A SIMULATION OF THE ECSS HELP DESK

WITH THE ERLANG A MODEL

THESIS

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Abstract

Innovation fuels change. In 2003, the Secretary of Defense established six transformational initiatives to optimize performance and improve efficiency across the Department of Defense. The Air Force responded with the Expeditionary Logistics for the 21st Century (eLog21) campaign plan. ELog21 drove the implementation for an Enterprise Resource Planning (ERP) system. The Expeditionary Combat Support System (ECSS) is the Air Force's ERP solution. A lot of literature focuses on the implementation of ERP systems, but there is a growing trend on ERP sustainment. Training and user support are a critical components to successful ERP implementations and sustainment. This thesis analyzes the ECSS help desk, and how projected staffing will affect the ability to provide support to users.

Help desks are classic queueing theory problems, and the Erlang C model is among the favorite models to use. Unfortunately, the Erlang C model has a reputation to overestimate staffing requirements. This study applies the Erlang A model through simulation, which accounts for the dynamics of customers who abandon their place in the queue. The results of this study show that staffing the level 1 and 2 tier help desks with 12 full time equivalents (FTE) each will yield the most efficient balance of customer wait times, call center agent utilization, and minimum abandonment.

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To My Family

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A SIMULATION OF THE ECSS HELP DESK WITH THE ERLANG A MODEL

I. Introduction

Overview

Innovation has been the backbone of United States. From the 1900s when Ford Motor Company used the assembly line to mass-produce automobiles at lower costs to the expansion of the internet in the 1990s revolutionizing the transfer of information, the United States has benefited from innovation. Today, companies leverage these innovations to conduct their day-to-day operations efficiently and effectively.

Both large and small companies continually invest in process improvement initiatives to improve efficiency, safety, and profits. The Department of Defense (DoD), follows the same path and continually seeks process improvement investments and initiatives to provide the taxpayer higher returns on their dollars spent on defense. In 2000, the United States General Accounting Office (GAO) acknowledged the DoD's logistics transformation initiatives outlined by the 1999 Logistics Strategic Plan. With the 30 pilot weapon system programs tested by the DoD, the GAO reported that many aspects of the overall transformation plan are incomplete. The GAO recommended that the DoD develop an overarching plan that will integrate each service's transformation plan with the Department-wide plan (GAO, 2000).

In 2003, the Office of the Secretary of Defense established six transformational objectives:

1. Optimize support to the warfighter
2. Improve strategic mobility to meet operational requirements
3. Implement customer wait time as a cascading metric
4. Fully implement total asset visibility
5. Reengineer applicable processes and systems to increase overall communication and operational situational awareness
6. Achieve best-value logistics while meeting requirements at reduced operating costs (ELog21 Factsheet, 2009).

The Air Force responded with a commitment to transform their logistics processes and systems by establishing eLog21, which stands for Expeditionary Logistics for the 21st Century. The main goal of eLog21 is to improve logistics support to the warfighter. The Air Force would accomplish this goal by improving processing in critical choke points in the supply chain, consolidating redundant systems, and realized cost savings through these initiatives (ELog21 Factsheet, 2009).

Enterprise Resource Planning Systems

One initiative rooted from the eLog21 initiative is the Expeditionary Combat Support System (ECSS). ECSS is an enterprise resource planning (ERP) system that will replace 420 legacy systems and standardize the Air Force's logistics process from end to end. Wenrich et al provided a solid definition of ERP systems:

> ERP systems are commercial software packages that embody and integrate any number of business processes involved in the operation of an organization including but not limited to manufacturing, supply chain,

> sales, financial, human resources, budgeting, and customer service activity (Wenrich et al., 2009).

The Oracle Corporation describes ERP systems as the control center for an entire organization. ERP systems collect data from each division and make them available throughout the entire company (ORACLE, 2009). For the DoD, ERP systems will facilitate the flow of information providing opportunities for savings and improved efficiency. In response to the initiatives, the Air Force pursued their own ERP system, ECSS.

Expeditionary Combat Support System Help Desk

ECSS is projected to have over 250,000 end users, and will go-live in 2012 with an estimated 40,000 users after initial release. In order to support and maintain this system, the Air Force will need to fund software support, project management, and support for the user. This paper will focus on the support needed for the end users, specifically the support provided by the help desk.

The ECSS help desk will provide support for 40,000 projected users through three tiers of support. The Field Assistance Service (FAS) located at Gunter Annex, Maxwell AFB in Alabama will provide Level 1 support. Level 1 support consists of basic assistance. If the Level 1 analyst cannot close out the trouble ticket, the call will be sent up to the Level 2 help desk. Level 2 and 3 support involves issues that are functional or technical in nature. The ECSS program management office (PMO) will be responsible for technical support, and the Air Force Logistics Management Agency will be responsible for functional support.

The ECSS PMO is currently analyzing the potential workload for the help desk. ECSS is a large-scale ERP implementation with very few comparable established ERP systems. The scale of the implementation limits the amount of data available to conduct a top-down analysis to determine the potential help desk workload. This limitation provides opportunities to conduct a bottom-up analysis of the help desk to forecast workload.

Purpose of This Study

This study evaluates the ECSS help desk through a bottom-up analysis using simulation and queueing models. Simulation is the primary analysis tool due to the limited data available. This study will explore the following research questions:

1. What is the most probable call volume for ECSS?
2. What are the probable staffing levels to match the projected call volume?
3. What are the optimal trade-offs between service quality and cost savings?

Summary of Findings

The ECSS help desk may experience call volumes ranging from 210 calls per day to 1,775 calls per day. This study found that 31 Level 1 and 2 agents is sufficient to handle the higher projected demands for user support when ECSS is implemented. Once users become more familiar with the system, and modifications have stabilized, about 12 Level 1 and 2 agents is sufficient to meet the steady state demand. Further along the life cycle, ECSS can reach a long-run state where the number of calls per user will decrease. At the long-run state, 8 Level 1 and 2 agents are sufficient. Adding agents to the estimate will yield slightly better performance but at a diminishing rate. This study recommends that Air Force leaders establish help desk performance goals for Level 1 and 2 and apply

the methodology used in this thesis to determine the staffing levels that best match their goals.

Chapter Summary

Innovation fuels success. In a continually evolving environment, companies and organizations must seek and fund transformational initiatives that will promote higher productivity and efficiency. Among the major innovations of the past decade are Enterprise Resource Planning Systems. ERP systems facilitate the transfer of information between divisions and departments in an organization driving efficiency and productivity.

The Department of Defense adopted a logistics transformation initiative to modernize logistics systems within the DoD. In response, the Air Force launched the acquisition of the Expeditionary Combat Support System. The implementation of ECSS ranks among the largest ERP implementations. High potential for returns are matched with numerous risks revolving around the performance, cost, and schedule. The Air Force will have to manage these risks through superior planning and analysis.

This chapter provided the driving force behind the ECSS help desk analysis. The literature surrounding ERP systems and help desk estimation are described in further detail in Chapter 2. Chapter 3 will discuss the data collected on help desk operations and the methodology used to design a working model to simulate. Chapter 4 will present the results of the study, and Chapter 5 will provide the ECSS PMO recommendations for standing-up a help desk.

II: Literature Review

Overview

The focus of this research is to forecast the workload requirements for the ECSS help desk. This chapter will present the relevant research, which will setup the foundation for the following chapters. The first section will discuss the costs and benefits of implementing an ERP system followed by the sustainment strategy with a focus on training and user support. The next section will discuss the dynamics of call centers to include industry best practices. The final two sections of chapter two will discuss research for queueing theory models and simulation techniques and their application to the call center.

Enterprise Resource Planning Systems

When a customer walks into a store and purchases an item, businesses would like to know certain aspects of the transaction such as item, amount, and time of purchase just to name a few. These data points allow that company to forecast demand, and the data can aid in key decisions such as reorder points and quantity to order. Imagine an environment where the actions of this customer trigger the producer of that good in a different country to increase output. The concept of seamless communication is a common practice sought after by many private and government organizations. ERP systems bring this scenario to life by supporting communication and cooperation throughout an organization and between its partners (J. Sarkis, 2003).

There is a wide range of literature pertaining to ERP systems. This section will focus on the effectiveness of ERP systems and the implementation. Critics have questioned the usefulness of ERP systems due to risks of high costs and varying potential

savings. Most ERP systems are major acquisitions that require a significant investment, so the benefits must outweigh the costs and risks before a company will commit. This section will show how the benefits can justify the risks of implementing an ERP system.

Benefits & Challenges

Mabert et al. wrote the article titled *Enterprise Resource Planning: Common Myths Versus Evolving Reality*, published in Business Horizons, discusses reasons why companies incorporated ERP systems into their organizations. The authors based the study on interviews of operational managers and IT personnel at large and small firms who have implemented ERP systems. Mabert et al. discus three general reasons dispelling common myths such as the Y2K spook. The first reason why companies adopted ERP was to simplify and standardize IT systems. Similar to the Air Force's current state, many companies had several legacy systems that did not synchronize creating inefficiencies. The second reason was to improve availability of information. With the necessary information readily available, leaders can analyze alternatives more efficiently. The third reason was to improve the quality of data (Mabert et al., 2001). Having data readily available is important, but so is accurate data.

Despite the three reasons listed by Mabert et al. concerning why companies adopted ERP systems, there are still huge hurdles such as high implementation cost. Mabert et al. stated that the cost of implementation among the sampled companies that they interviewed ranged between 1.5 percent and 6 percent of annual revenues. Smaller firms ranged from 3 to 6 percent and larger firms ranged from 1.5 to 2 percent. Of this percentage, the bulk of the cost came from consulting at 30%, hardware at 25%, and training at 15% (Mabert et al., 2001).

The cost categories discovered in the interviews also make sense for ECSS since the system will be a COTS system with several modifications that will require new hardware that can handle the demand. All users will need training at the different service levels, and with 250,000 projected end-users, training will have a significant impact. Consulting is a given with any major DoD system implementation requiring expert support. The DoD utilizes external contractors and consultants for this expert support.

The results from the survey conducted by Mabert el al. are mostly positive. Table1 breaks out the pros and cons of ERP systems on large and small firms:

Table 1: ERP Pros & Cons

Pros	Cons
Lower inventories	Expensive Implementation
Improved Delivery Schedules	Not an end-to-end solution
Increased Productivity	Mix response on cost reductions
Simplified and standardized systems	
Can handle transaction processing even in very large companies	
Improved data availability and quality	
Many companies expect the useful life to to exceed 10 years	

(Mabert V.A et al., 2001)

A thesis at the Air Force Institute of Technology written by Craig A. Lane discussed the pros of an ERP system at a more detailed level. Lane adapted a chart from Pal Bose, the author of an article that analyzed the benefits of an ERP system for a Chinese valve manufacturer, which outlines the benefits that the company realized from the system (Lane, 2009). Table 2 lists the benefits.

Table 2: Benefits of an ERP Implementation at Neway

Operational measures	Pre-implementation	Post-implementation
Commitment to fulfillment	80%	98%
Average lead time	45 minutes	30 minutes
On-time delivery percentage	80%	95%
Average safety stock period	40 days	25 days
Inventory accuracy	85%	99%
Average monthly purchase frequency	50	10

(Lane, 2009)

The table shows that the valve manufacturing company saw improvements in lead-time, on-time delivery, decreased safety stock, inventory accuracy, and less purchase frequency. Overall, these improvements will improve operations and increase profit. Lane also discussed the improvements realized by the Defense Logistics Agency (DLA) with their implementation of their Business Systems Modernization (BSM). Table 3, which came from Lane's thesis, shows these benefits

Table 3: Benefits of BSM at DLA

	FY 2000	FY 2007
Cost of Operations	22.1%	13.1%
Average Order Processing Time	> 1 work day	< 4 hours
Overall Material Availability	88%	92%
End-of-Year Financial Close-out Time	2 weeks	1 day

(Lane, 2009)

Table 3 shows that the DLA realized a decrease in cost of operations, improved order processing time, material availability, and decreased end-of-year financial close-out time. The common themes once again from these two studies are the improvements in operations, processing orders, and reliability; and the decrease in inventory, processing time, and costs (Lane, 2009). The Air Force could see improvements in the same areas with the correct implementation of an ERP system.

Studies have shown both positive and negative effects of ERP systems. Robin Poston and Severin Grabski conducted a study comparing firms' performance ratios

before and after ERP implementation to determine the financial impacts of ERP systems. They concluded:

> Based on the sample of 50 companies implementing ERP packages from 1993 to 1997, results indicate no significant change in costs as a percentage of revenue until 3 years after the implementation of the ERP system, and then a significant decrease in costs only for cost of goods sold as a percentage of sales. There were no significant decreases associated with selling, general, and administrative costs scaled by revenues, nor was there any improvement in RI. However, there was a significant decrease in the number of employees as a percentage of revenue all 3 years after ERP implementation. While inconclusive, this paradox suggests additional complexities surround ERP technology. To fully understand the results, the limitations associated with the study must be examined. (Poston et al., 2001).

The main limitation with their research was the three-year longitudinal window. The three-year window is a limitation because many ERP systems may require a longer period before companies realize benefits. In addition, it is undetermined whether the ERP systems are the main driver behind increased performance. Companies could also attribute increased performance from the bolt-on applications added to an ERP system or from the company's transformation initiative that led to an ERP implementation (Poston et al., 2001). Bolt-on applications are custom developed software solutions that users add to ERP systems to fulfill a specific function.

Hunton et al. conducted a follow-up study and compared the performance of ERP adopting firms with the performance of firms that did not adopt an ERP system. Hunton et al. determined that firms who adopted ERP systems in general, outperformed those that did not in terms of return on assets (ROA), return on investments (ROI), and asset turnover (ATO). In addition, they analyzed the impacts of ERP systems on both large and small firms and healthy and unhealthy firms. Hunton et al. confirmed that the impact of an ERP system would be greater for small firms and unhealthy large firms. The

productivity paradox for IT expenditures could be a reason why large healthy firms do not see a net gain in revenue. The paradox states that the efficiency gains in some areas counter higher costs in another area (Hunton et al., 2003).

Although mixed reviews about the impact of ERP systems exist, the consensus is that benefits do exist. Some of these benefits discovered through the literature review are lower inventories, standardized systems, decreased safety stock, and decreased cost of operations to name a few. For the Air Force, the main risk is investing resources into a system that will not improve operations. To mitigate this risk, ECSS will require a well-planned implementation and continuous support throughout the lifecycle.

Sustainment

Implementation of ERP systems has received a lot of attention, but the maintenance, sustainment, and support of ERP systems has not been as widely studied. Annual maintenance costs approximate 25% of initial implementation costs. This has caused some to question why this subject has not received greater of attention (Sui Pui Ng et al., 2003). With annual maintenance and support cost averaging 25% of initial implementation and assuming a potential useful life of ERP systems at around 10 years, it is clear that a company will expend more resources on maintenance and support than on acquisition and implementation.

Kristi Wenrich from Penn State published a case study on an anonymous large company with a decade of experience and two major upgrades. In her article, Wenrich emphasizes the importance of user support. "Organizations sustaining ERP implementations can expect a larger part of their maintenance work from user support and investigation requests than a team supporting an in-house developed software

package" (Wenrich, 2009). Wenrich made the point that repeated system training counters the higher demand for user support, but this solution could be a less cost effective alternative for the Air Force when compared to establishing a help desk to supplement training. Sui Pui Ng et al. also emphasized the importance of support and specifically the help desk by incorporating the help desk in their preliminary ERP Maintenance Model listed in Appendix A (Sui Pui Ng et al., 2003).

Btissame Iba, from Cranfield University, presented a top-down model outlining the life-cycle stages in Figure 1:

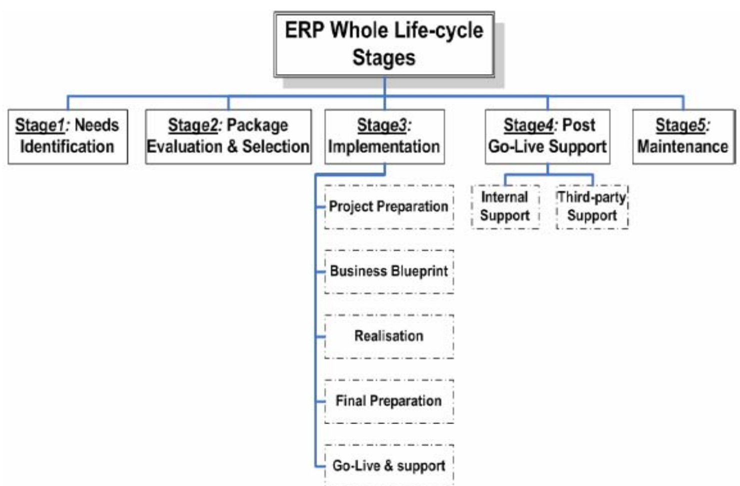


Figure 1: ERP Whole Lifecycle Stages **(Iba, 2006)**

Iba's research emphasizes the importance of support, and it breaks out the support into two categories. The first category is the initial stage where the system goes live and support teams assist users with utilizing the new system. The second category is the remaining life cycle support post implementation. Iba along with other authors like Wenrich have discussed the support decision whether to provide support in-house or outsource support to leverage expertise (Iba, 2006). ECSS without a doubt will outsource

some support, but the degree of outsourcing is variable dependening on several factors like .

The literature for ERP systems supports the implementation of ECSS, but the success of the implementation will be highly influenced by the Air Force’s utilization of industry best practices. In addition to implementing the new software, life cycle costs of ECSS will consume the majority of resources allocated for the system, so a detailed review of the planning and programing phases are necessary. In particular, the Air Force should consider the impacts of training and support to enhance utilization of the system.

ERP Help Desk

Although help desk support is not the main driver of sustainment costs for most ERP systems, decision makers sometimes overlook and under estimate the direct and indirect impacts of a help desk. The direct impacts are costs from staffing, facilities, and software/hardware requirements. Failure to have an adequate formal support structure can lead to unintended consequences such as informal methods of learning as well as affect the initial buy-in of users (Boudreau, 2003).

One of the most import measures of a successful launch of an ERP is the utilization of the ERP system by its users. Marie-Claude Boudreau challenged the statement that the users will use a successfully implemented ERP effectively. Boudreau discovered that successful implementation and effective use were not synonymous through her case study of a state government institution in the United States (Boudreau, 2003).

Boudreau mentioned that learning was a key predictor of system use. She broke out learning through formal and informal training. For the company in Boudreau’s case

study, initial training was setup but was ineffective since leadership did not mandate that all users attend training. For users who did not attend training, the alternative was self-help and the use of the help desk. In this case, employees did not find the help desk very useful due to the incapability to respond to user requests in a timely fashion. The cause of the slow response times was inadequate staffing at the help desk (Boudreau, 2003).

Unfortunately, researchers have not published much work regarding the relationship with ERP systems and the help desks that support them. The literature for ERP implementation and sustainment has been discussed in this section, which has established the importance of user support for ERP systems. User support includes training and the help desk. The next section will introduce the dynamics of a help desk and applicable best practices for ECSS.

Help Desk Research

Help desks fall under the category of call centers. Call centers define resources used to deliver service through the telephone (Gans, 2003). Call centers provide many services like customer service, emergency response, and tele marketing. In the current environment with varying forms of communications, experts define some call centers as contact centers since they handle issues through multiple mediums such as phone, email, text, fax, and chat. The added dimensions of a contact center make the use of queueing models more challenging. This research will focus on the application of current call center models with ECSS.

When discussing call centers, there are inbound, outbound, and hybrid call centers. Inbound call centers receive calls from customers like help desks or customer service. Outbound call centers focus on contacting customers and make more outbound

calls than receive calls, such as telemarketers or political campaigns. Finally, hybrid call centers combine both disciplines. The ECSS help desk will be primarily an inbound call center with the capability of a contact center for higher levels of support.

With new developments in technology, call center models have become more complex by leveraging automation and customer routing. The following diagram on Figure 2 by Gans et al. gives a good model of a typical help desk. The following paragraph explains each piece of the model.

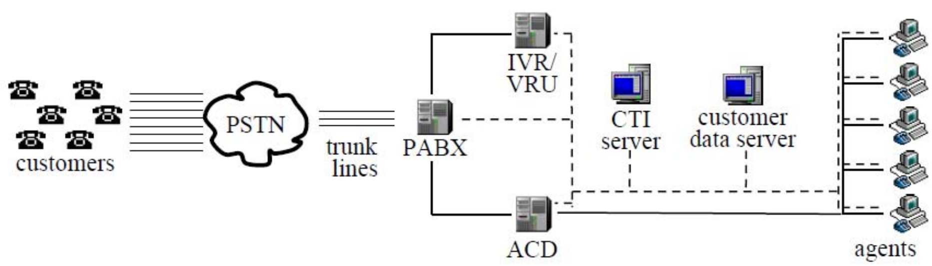


Figure 2: Schematic Diagram of Call Center Technology (Gans et al., 2003)

Customers enter the system when they dial the telephone number. From that point, the customers enter the public service telephone network (PSTN), the customers are identified by their telephone number, and are routed to the company's private automatic branch exchange (PABX). The trunk lines connect the PSTN with the PABX, and the company usually owns these lines. The PABX routes customers to the interactive voice response (IVR) unit where the system gives the customer options that will determine which agent they will be assigned to through the automatic call distributor (ACD). The computer-telephone integration (CTI) server collects and matches data on the customer and displays the information for the agent (Gans et al., 2003).

Once customers have entered the system, the system will route them to the appropriate agent. Agents in most help centers are divided into areas of expertise and levels of knowledge. For some help desks, level-one agents have general knowledge of the system and handle basic request like password resets and profile changes. Level-two and level-three agents handle issues that are more complex.

Apart from the operations of the call center, help desk managers must balance agent schedules with customer demand to optimize service and minimize costs. Math models have been used to estimate and forecast requirements for call centers. Through certain assumptions, managers can quickly calculate key figures like average wait time and agent utilization factors. These are queueing models and have a wide range of applications. The next section will discuss queueing models and apply them to call centers.

Queueing Models and Call Centers

Queueing theory is the mathematical theory of waiting lines (Cooper, 2003). Many problems that utilize queueing theory revolve around service-focused operations like determining the number of tellers to use at a bank or the number of cashiers to service customers at a store during peak shopping season. The basic assumptions are that the arrival and service rates are a stochastic process (random) with the Markov property (memoryless). Experts use the Kendall notation system to describe queueing models. The notation describes a queueing model’s three basic characteristics (Ragsdale, 2007). The basic characteristics are:

Arrival Rate - λ

This characteristic defines the number of arrivals during a given period. The arrival rate can take on different distributions, but a popular distribution is the exponential distribution as shown in Figure 3.

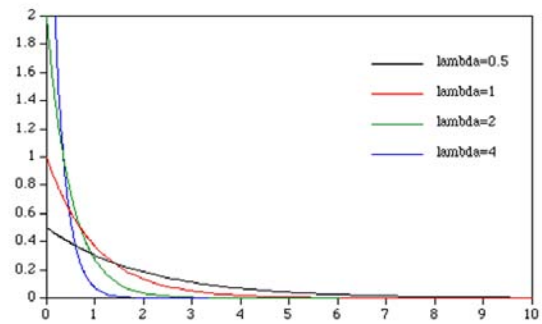


Figure 3: Exponential Distribution (Bourke, 2001)

Exponential distributions play a key role in queueing models because of their memory-less property, also known as a Markov process (Ragsdale, 2007). If a call center process is memory-less, the amount of time that has passed since the last call does not influence how much time will pass until the next call arrives. Applying this to the ECSS help desk, the arrival rate takes on this memory-less property since a peak or low point in arrivals will not affect the arrival rate for the next customer.

Service rate - µ

According to Ragsdale, “Service time is the amount of time a customer spends at a service facility once the actual performance of service begins” (Ragsdale, 2007). Analysts usually model service time as an exponential probability distribution that is a stochastic process with the Markov property similar to the arrival rate. The great property the exponential distributions have is the ability to hold the same distribution as the model adds other exponential distributions to the system. For example, when the

system adds a second server to a help desk, the service rate will still hold an exponential distribution, also known as the property of infinite divisibility. The journal *The Annals of Mathematical Statics* publishes a copy of the proof of infinite divisibility (Katti, 1967).

Number of Servers - s

The number of servers is the final key characteristic defined by the Kendall notation. The variable is self-explanatory, but the challenge arises when analysts are faced with varying server amounts and server levels like a help desk. When call volume increases for a help desk, more people (servers) log into the system to assist customers. Each technician has different service rates depending on their specialty or proficiency in the case where the organization has trained all agents to handle all types of calls. In order to simplify calculations, analysts assume equal service rates among servers. Yamashiro analyzed the system of queue-dependent servers originally analyzed by Singh and Garg. In this article, Yamashiro discusses the derivations of equations that capture the state where the queue length reaches a certain number N and another server is introduced to the system to meet the growing queue (Yamashiro, 1996).

Queueing Models

One of the most familiar queueing models is the M/M/S model, also known as the Erlang C model. “Queueing theory was born in the early 1900s with the work of A. K. Erlang of the Copenhagen Telephone Company, who derived several import formulas for tele traffic engineering” (Cooper, 2003). A. K. Erlang derived the Erlang C model, also referred to as the Erlang delay model, along with several other models like the Erlang loss model (Cooper, 2003).

The Erlang C model has an exponential arrival rate, exponential service rate, and s number of servers. With these assumptions, one can calculate certain characteristics like the average number of customers in the system, average time a customer spends in the system, and the utilization factor for the system. Appendix B lists the formulas for an M/M/S model in terms of the following variables:

λ - The arrival rate of customers

μ - The service rate of each server

κ - The number of customers in the system

One of the many benefits of the Erlang C model is the ease of calculations with the application of Little's Law. Little's Law says, "the average number of items in a queueing system equals the average rate at which items arrive multiplied by the average time that an item spends in the system" (Little, 2008). The following equation represents Little's Law:

L = Average number of items in the queueing system

W = Average time spent waiting in plus the service time

λ = Average Number of items arriving per unit time

The downsides of the Erlang C model are the assumptions made of fixed exponential service rates and ignoring certain aspects of call center dynamics. The issues that this research will address are single-type single-skill, constant staffing, abandonment, retrials, and time-varying conditions (Gans et al., 2003).

This section will examine alternative queueing models to determine the variances for predicted values. Busy signals and abandonment add a different dimension to queueing models, so the M/M/N/B + G and the M/M/N/B + M models were created to capture the trade-offs between busy-signals, delays, and abandonment. B stands for the number of lines, +G stands for patience with an assigned distribution, and the final +M stands for patience with an exponential distribution. Garnett et al. discuss the derivations of the proofs for the M/M/N + M model, also known as the Erlang A in the article *Designing a Call Center with Impatient Customers* (Garnett et al., 2002). In the Erlang A model, the A stands for abandonment.

In the article, Garnett et al. shows the impacts of ignoring abandonment in call center forecasting. In their article, they state, “The immediate effect of an abandonment is less delay for those further back in line, as well as for future arrivals … using workforce management tools that ignore abandonment would result in over-staffing as actually fewer agents are needed in order to meet most abandonment-ignorant service goals” (Garnett et al., 2002). Chapter 3 of this report will discuss the performance measures and parameters for the M/M/N+M model.

In call center forecasting, a common principle to follow is the square root rule for safety staffing. According to the rule, Equation 1 represents the appropriate level of staffing:

Equation 1:

The equation represents the offered load, and β represents the desired level of service. Generally, the ratio of arrival rate and service rate is less than or equal to one for systems capable of reaching equilibrium, and under the standard M/M/S model a ratio of

1 would most likely yield an unstable system. Beta is the safety factor in the equation since a system with a steady and predictable arrival rate would only need the minimum number of agents represented by R. With abandonment, the square root rule still holds true. Garnett et al. show that the rule holds by modifying the formula for β by incorporating abandonment. As the rate of abandonment increases, the capacity needed to meet the desired service level decreases (Garnett et al., 2002).

Garnett et al. take the staffing level formula a step further by introducing three staffing regimes in Table 4. The difference between the quality and efficiency-driven regimes with the rationalized regime is that ϵ determines the staffing level, a fixed percentage above or below the offered load. Since ECSS will require a modest staffing level, the rationalized or quality-driven regime might work well for the level 2 help desk and the Level 1 can implement a rationalized strategy since agents will most likely handle additional systems.

Table 4 System Performance in Three Staffing Regimes

Regime	Staffing Level	Performance Characteristics
Rationalized	$N = R + \beta\sqrt{R}$	$P\{W > 0\} \to \alpha(\beta)$ and $P\{Ab\} \to 0$
Quality-driven	$N = R + \epsilon R,\ \epsilon > 0$	$P\{W > 0\} \to 0$ and $P\{Ab\} \to 0$
Efficiency-driven	$N = R - \epsilon R,\ \epsilon > 0$	$P\{W > 0\} \to 1$ and $P\{Ab\} \to \epsilon$

(Garnett et al., 2002)

With a higher rate of abandonment, the required capacity to match the server level is less. Customers abandon their place in the queue for many reasons, such as a preference to reenter the system at a more convenient time or the expiration of patience. The question that researchers must ask when using these complex queueing models is whether their benefit is significant. Garnett et al. show their significance in high volume

call centers, but what about lower volume help desks in the case of ECSS where the previous estimates for call center technicians is far less than that of a major call center such as United Airlines? The additional dimensions of abandonments, delays, and re-trials could be influential in some cases, which is why simulation will be the main analysis tool.

Statistical Analysis and Simulation of Call Centers

Call centers are data intensive operations where empirical analysis can be a very reliable method to predict future outcomes. A few research papers have addressed the statistical analysis of call centers and simulation, and many of these research efforts provided useful and insightful results to the customers. This section will discuss the literature pertaining to call center statistical analysis and simulation.

Statistical Analysis of Call Centers

A few challenges arise when applying statistical analysis to call centers. A major challenge is to collect comprehensive data to validate certain assumptions and test new hypothesis, since few published articles have analyzed full call center datasets. The article, *Statistical Analysis of A Telephone Call Center: A Queueing-Science Perspective*, by Brown et al. discusses their findings from a bank's call center data. In their article, Brown et al. test three major assumptions: call arrivals, service duration, and customer patience (Brown et al., 2005).

A common method for estimating call centers is to assume that call arrivals follow a Poisson process with different rates at specific blocks of time. In other words, they tested the assumption that the rate of arrivals into the system vary over time rather than remain uniform. Brown et al. tested the null hypothesis that arrivals form an

inhomogeneous Poisson process. With the given dataset, they failed to reject the null hypothesis showing the strength of the assumption that the rate of arrivals is a function of time (Brown et al. 2005).

The second assumption Brown et al. tested was the exponential distribution of service times. Brown et al. had to account for a slight abnormality with the data shown in Figure 4 referred to as agent abandoning, which is represented by the spike at zero. Agents hanging up on callers in order to have a longer break period caused this phenomenon.

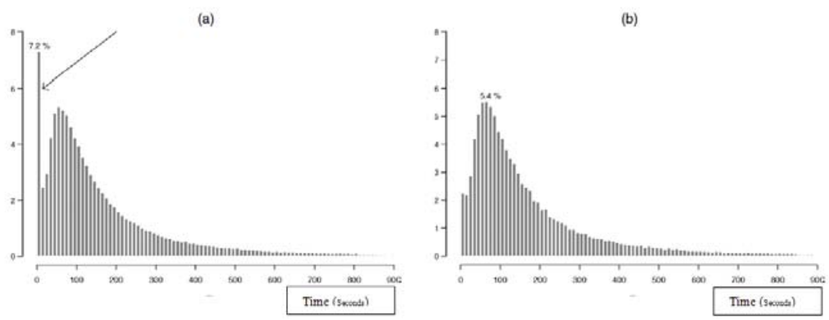


Figure 4 Agent Abandoning (Brown et al., 2005)

The results of their analysis rejected the null hypothesis of exponentially distributed service times. After the agent abandoning correction, the data fit a lognormal distribution well contrary to the initial assumption that service times fit an exponential distribution (Brown et al., 2005). The challenge with fitting a lognormal distribution to this study is the standard deviation data was not available for the analogous and legacy systems. Chapter 3 will discuss the data collected and the limitations with the data.

The third item Brown et al. discussed was the finding of a study by J. Kingman titled *On Queues in Heavy Traffic, I and II.* The study found that in heavy traffic, waiting time is exponentially distributed. Brown et al. tested the same assumption in the 2002

version of their article and confirmed the findings (refer to Figure 5 for their graph) (Brown et al., 2002).

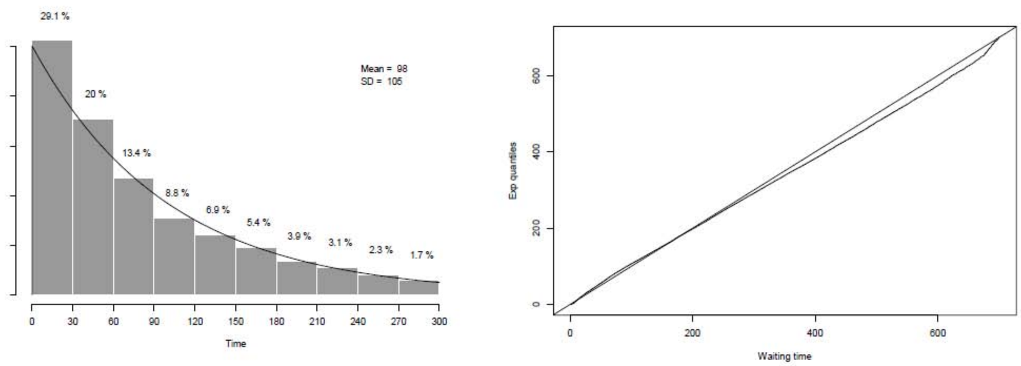


Figure 5 Distribution of Waiting Time (Brown et al., 2002)

The foundation of this study is the simulation of the queueing models. The simulations will produce a set of data, and regression analysis will be used to determine the relationships of the independent variables of number of agents, arrival rate, service rate, and customer patience with the independent variables. The independent variables for this study are average waiting times, agent utilization rates, and the ratio of customers that renege.

Simulation

Simulation is a cost effective method for modeling risk and uncertainty. This section will discuss the published literature using simulation to model call centers and IT systems. Lisa Fitzgerald and Tiffany Harper discussed simulation in their article titled, *The Application of Simulation Modeling for Air Force Enterprise IT Transformation Initiatives*. Fitzgerald et al. mentioned high returns on investment with modeling and simulation (M&S). M&S allows analysts to test the effects of ERP workloads and infrastructure, but managers have not utilized M&S for Enterprise applications (Fitzgerald et al., 2008).

Miller et al. showed the benefits of simulation in a business case projecting ROI. In their study, the company implemented a new call routing technology across 25 call centers. The investment costs were $17 million and operating costs were $8 million. The goal was to determine whether the cost savings would justify the investment. Miller et al. listed the following benefits of the M&S approach: controlled environment, ease of changes to model, cost effective, supportable extrapolation, and ease of modeling other influencing factors. Their study concluded that the cost savings with the new technology was dependent on call volume, so the company adopted a strategy that incorporated two routing technologies (Miller et al., 1999).

Vijay Mehrotra, professor at the University of San Francisco, and Robert Saltzman, professor at San Francisco State University, have accomplished insightful research on call center optimization through simulation. A valuable aspect to their research is their use of the ARENA simulation package on call centers, which is the simulation package used in this study. In 2001, Saltzman and Mehrotra published a study where they assisted a large software company determine the feasibility of a new program through an ARENA simulation. In their simulation, they modeled two priorities for arriving customers and call abandonment (Saltzman et al., 2001).

Saltzman and Mehrotra encountered similar challenges faced in this study such as the lack of detailed distribution data for the service rate and abandonment behavior. They assumed that the service rate fit an exponential distribution, and abandonment fit a linear function over time based on wait time. The likelihood of abandonment would increase by 3.5 percent for each additional two minutes of wait time, with a maximum abandonment percentage set at 40 percent. Through their model, Saltzman et al. were

able to simulate 36 scenarios and influenced the company's decision to incorporate the new program. Through the simulation, the company was also able to determine the key points when to add agents to the call center to meet target goals (Saltzman et al., 2001).

Mehrotra and Fama wrote an article discussing methods, challenges, and opportunities for call center simulation. In the article, Mehrotra et al. discuss the reasons why call centers turn to simulations, major ways call centers utilize simulation, and typical inputs modeled in call center simulations. The section discussing typical inputs modeled was very useful for this study, which models the ECSS help desk. Mehrotra et al. confirmed the challenges with ACD data leading to the assumption of exponential handling times. They also discuss key parameters about the agents in the call center such as their skills, schedules, and shrinkage factors on utilization rates. For this study, agent skill will be modeled since the agents from the ECSS level I and II help desk will have different service rates. Shrinkage is the factor applied to capture unscheduled lost agent time. This phenomenon is linked to scenarios like unexpected absences, longer than expected breaks, or late arrivals. In the example cited by Mehrotra et al., they apply a shrinkage factor of 10% (Mehrotra et al., 2003).

Finally, Mehrotra et al. discuss key inputs for modeling abandonment. One of their key observations is the "great differences in customer behavior across different industries and different companies' operations" (Mehrotra et al., 2003). In their example, Mehrotra modeled the customer's tolerance for waiting as an exponential distribution as recommended in the 2002 article by Garnett et al. previously discussed in this chapter.

Chapter Summary

This chapter presented the relevant literature necessary to outline the basic purpose of an ERP system. ERP systems facilitate the transfer of information, whether it is for the analysis of future decisions or streamlining operations, but these benefits come with risks such as high implementation costs. This chapter showed that the benefits could outweigh the costs of implementing an ERP system over a period while providing better performance and fewer labor requirements. A lot of research has focused on the implementation of ERP systems but there is a lack of research analyzing the sustainment costs of these systems. Annual sustainment costs can average 25% of the initial implementation costs giving it a higher life-cycle cost than the implementation.

A subset of sustainment is training. Once ECSS goes live, there will be initial training to stand-up the system and on-going training to refresh users, train new users, and provide training for upgrades and modifications. The ECSS help desk will support training at all stages and is an important factor to successful operations. This chapter presented the dynamics of help desks and the relationship of help desks with training. The research discussed the application of simulation and queuing models for call center forecasting, and it presented the Erlang-A model, which accounts for callers' impatience. The Erlang A model is the main queueing model used in this research and the following chapter discusses the methodology in detail.

III: Data Collection and Methodology

Overview

There are several methods used to forecast call center traffic. This chapter will discuss the different methods and describes the techniques used to forecast the performance of the ECSS help desk. The first section will discuss the data collected through prior research and the current study. The research will use the data analyzed to provide the performance parameters used in the models and simulations. The following section will discuss the queueing models in the analysis. The next section will describe the methodology used to simulate the ECSS help desk. Finally, the report will discuss prior estimates and conclude with the chapter summary.

Data

Call centers are data intensive whether they are large call centers with over 100 agents or specialized technical help desks with only 10 agents. Call centers collect operational data like average handling time and average speed to answer. This section will define the operational data collected; discuss the data's impact to call center operations; and describe the help desk data collected for this research. The data collected came from several help desks operations organized with the following categories: the current ECSS help desk, legacy logistics systems, and analogous ERP systems. This section will provide insight on the influence of data on call center forecasting.

Data: Descriptions

Call center operational data tracks the performance of the system and gives managers the information to analyze major decisions like staffing, scheduling, and structure. This section lists and defines the type of call data collected:

Calls Received: The total number of calls arriving to the system. When analysts represent calls received as a rate over time, this becomes the arrival rate signified by λ in queueing formulas. With all other variables held constant, as the arrival rate increases so does the traffic intensity of the system. If the traffic intensity exceeds the service rate and capacity of the system, customers will experience very long wait times and may baulk.

Calls Answered: This metric tracks the total number of calls entering the system and answered by an agent. The difference between calls received and calls answered shows the customers that left the system while waiting. The case, presented in chapter 2 where servers abandon customers, can skew the calls answered since it represents a better service rate than the system's actual performance.

Abandonment rate (ABA): ABA tracks the rate of calls received that abandon the system before reaching a service representative. The abandonment rate influences the operations of a call center because as customers leave the system, the waiting time reduces for customers in the queue and those that are about to enter. Most call centers only track the abandonment from the period when the customer enters and leaves the queue. This method does not accurately represent total abandonment because the customers that enter a different queue after initial service are not included in the metric. The Erlang A model captures abandonment through the patience variable, Θ. Through simulation, this study will capture the full dynamic of abandonment.

Average Speed of Answer (ASA): This statistic is also known as the average time to answer. ASA captures the average amount of time it takes for a customer entering the system to reach a call center agent, which also represents the average time that a customer spends in the queue waiting for service. W_q or E[W] in most queueing calculations is the same metric as ASA.

Average Handling Time (AHA): This variable captures the average time that a customer spends with a call center agent or the service rate represented by μ in queueing models. Through Little's Law presented in Chapter 2, the service rate and arrival rate set the foundation to calculate performance measures such as utilization factor, average time a unit spends in the system, and average number of units in the system.

Data: Current and Legacy Systems

With the call center data defined, the study can describe the sources of data and the types of data collected. One source of data came from the current ECSS help desk, which average 0.38 calls per user per month. In an ideal call center estimate, analysts would use historical data to project workload. This method will not be reliable with ECSS because the help desk was just recently established and many changes are still influencing the call data. Another limitation of the ECSS help desk data is that the system is operating on a small scale and technicians are working through major fixes and bugs with the software, which will most likely represent a low arrival rate but a long service time.

The ECSS help desk assigns a priority level to certain incidents, which violates the queueing assumption of homogeneous customers and first-in-first-out. The dataset

tags calls with the username, location, server identification, begin time, end time, and a problem description. Technicians do not close the majority of incidents until several days after the incident opened making it difficult to determine an actual service rate. With the limited period and scope of the current ECSS help desk, this report will use the calls received data to compare with other call volume estimates for the level II help desk in Chapter 4.

The bulk of the data for this section came from legacy logistics systems that the Air Force projects ECSS to replace in the future. The data covers the period of 2004 to 2010 and captures the steady state performance once a system has been established. Table 5 lists and describes the legacy systems used.

Table 5: ECSS Legacy System Identifier

System	Acronym	Description
Enterprise Solution-Supply	ES-S	The Enterprise Solution-Supply online tool gives logisticians the ability to find parts stored in any of the more than 300 Air Force depot- or base-level supply accounts with a single query that processes in seconds. <http://www.afmc.af.mil/news/story.asp?id=123012384>
Mobilitiy Inventory Contral and Accountability System	MICAS	USAF inventory management system that tracks shelf-life visibility of stored and issued assets, can verify serviceability of assets, provides capability to roll-up asset visibility, ands provides full suite of barcode production and scanning. <www.dtic.mil/ndia/2003chemical/ens.ppt >
Standard Base Supply System	SBSS	A computerized system to account for supplies and equipment at the base level <http://www.af.mil/shared/media/epubs/PUBS/AF/23/23011002/020201/020201.pdf>.
Standard Asset Traching System	SATS	Improves base level asset tracking and reduces paper work using barcoded labels, identification numbers, and passwords <http://www.af.mil/shared/media/epubs/PUBS/AF/23/23011002/020501/020501.pdf>.
Combat Ammunition System	CAS	An Inventory ammunition inventory management system <http://faculty.ed.umuc.edu/~meinkej/inss690/burns.pdf>.
Tool Accountability System	TAS	This system is the primary means for accountability and to track and control the location of tools and equipment stored and issued <http://www.af.mil/shared/media/epubs/TRAVISAFBI21-107.pdf>.
Cargo Movement and Operations System	CMOS	Automates information management in receiving, shipment planning, packing and crating, and air/surface terminal work centers during normal operations and transportation mobility operations during wartime/crisis situations. <http://www.tis.army.mil/PS_Cargo_Movement.htm>
On-Line Vehicle Interactive Management System	OLVIMS	This systems tracks the consumption of vehicles and collects the data in a standard database and system for queries and analysis <http://www.aflma.hq.af.mil/shared/media/document/AFD-100120-052.pdf>.
Integrated Maintenance Data System	IMDS CDB	The standard Air Force system for maintenance information. IMDS functions as a single logical data base that accesses historical and legacy data currently stored in other data bases <http://www.globalsecurity.org/military/library/budget/fy1998/dot-e/airforce/98imds.html>.

The ECSS analysis team collected most of the data for the legacy logistics systems. One of their main sources is the Field Assistance Service (FAS), who handles the majority of level I calls and a few level II calls. The remaining data for legacy logistics systems came from the individual program management offices. The majority of program management offices handle level II calls.

This study collected call data from the FAS from two sources. Two datasets came from the ECSS PMO's previous datasets, and the third came from the FAS in the form of a presentation. The first set covers operations from 2004 through 2010, which are composed of all the systems in Table 5 except for IMDS. The data are cumulative for number of users, calls, calls passed to level II, months of data, and years of data for each system. Analysts calculated averages and percentages from the given data. Table 6 lists the data:

Table 6 FAS 2004-2010 Legacy System Data

Program	Users	Calls Per User Per Month	2004-2010 Total Calls	2004-2010 Calls Passed to Level II	2004-2010 Percentage of Calls Passed to Level II	2004-2010 Months of Data	Years of Data
ES-S	15,212	0.004	4,170	1,794	43.0%	63	5.25
MICAS	3,000	0.007	624	449	72.0%	29	2.42
SBSS	4,768	0.029	9,211	4,156	45.1%	67	5.58
SATS	4,500	0.008	2,364	1,711	72.4%	67	5.58
CAS	12,256	0.016	13,430	3,836	28.6%	67	5.58
TAS	15,000	0.026	26,396	4,108	15.6%	68	5.67
CMOS	2,118	0.335	47,569	27,014	56.8%	67	5.58
OLVIMS	3,840	0.044	11,382	2,940	25.8%	67	5.58
Totals	**60,694**		**115,146**	**46,008**	**40.0%**	**495**	**41.25**

The report will use this data in the following chapter to estimate arrival rates for level I and II help desks through an average call rate per user. The thesis addresses the challenges associated with this approach. The first challenge is determining if the analysis will use a factor to account for the possibility that some of the users in this dataset are users for multiple systems. If the ECSS analysts summed up the average calls

per customer for each system, the average calls per user for ECSS could be higher than what the help desk will experience. On the opposite end of the spectrum if analysts take an average of the average calls per user, the average calls per user for ECSS might be significantly lower since ECSS is composed of several multi-functional modules that will require a higher proficiency from users. Each system has a different level of complexity and dynamic that creates the demand for users to call the help desk at varying rates.

The second dataset from the FAS covered level I and II call data for 2010. The legacy systems in this dataset are the CAS, CMOS, ES-S, IMDS, OLVIMS, and SBSS. The data shows total service duration per system for year 2010. Table 7 lists the mean and median call durations for each system broken out by level I and II. The data also calculates the average calls per month and the average calls per user per month. Table 7 shows the second set of data collected from the FAS:

Table 7 2010 FAS Call Summary

System	# Users From Prior FAS Data	# Level I Calls	Total Level I Time In Minutes	Level I Median Duration	Level I Mean Duration	# Level II Calls	Total Level II Time In Minutes	Level II Median Duration	Level II Mean Duration	Estimated Level I FTEs	Estimated Level II FTEs	Percentage of Calls Handled By Level II Help Desk
CAS-B	12,256	1,680	50,427	14.00	30.02	532	13,541	10.00	25.45	0.5	0.1	24.1%
CMOS	2,118	8,678	161,448	14.00	18.60	1,968	29,255	10.00	14.87	1.5	0.3	18.5%
ESS (ILS-S)	15,212	1,253	16,098	9.00	12.85	332	2,818	3.00	8.49	0.1	0.0	20.9%
IMDS CDB	234,917	7,810	146,032	16.00	18.70	5,307	96,157	10.00	18.12	1.3	0.9	40.5%
OLVIMS	3,840	2,748	42,906	12.00	15.61	607	15,835	15.00	26.09	0.4	0.1	18.1%
SBSS (Base Supply)	4,768	1,173	16,180	10.00	13.79	547	7,261	5.00	13.27	0.1	0.1	31.8%
Totals	**273,111**	**23,342**	**433,091**	**14.00**	**18.55**	**9,293**	**164,867**	**10.00**	**17.74**	**3.9**	**1.5**	**28.5%**

The final data received from the FAS came in the form of a presentation. The data captures abandonment (ABA) and the wait time (ASA) percentages. The limitations of this data are listed as follows:

- The presentation did not break out the metrics by system
- The presentation does not show the mean and standard deviations
- The sample covers only one year of operations.

To work around these limitations, the analysis will incorporate the mean and standard deviation abandonment wait times from the Brown et al. article where they analyze call data from a bank's call center. The challenge with this approach is that the research must assume that the callers for the bank's call center have similar patience as the callers for the ECSS help desk. Table 8 presents the data from the Brown et al. study in seconds and is truncated at 15 minutes.

Table 8: Customer Wait Time Before Abandoning in Seconds

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean	68	76	119	109	96	85	105	114	84	73	101	111
SD	67	78	126	108	101	89	105	119	89	83	109	116
Med	46	50	75	72	62	55	69	72	54	45	63	71

(Brown et al., 2002)

The data collected from the FAS shows operational data for legacy systems that ECSS will replace. The data covered periods from 2004 through 2010. Two out of the three sources of data came strictly from 2010. A limitation with the collected FAS data is the inability to access the full dataset, which would show individual call data. Without the individual call data, this report cannot apply statistical tools and tests such as analyzing variance and determining distributions.

Data: Comparable Systems

Using data from legacy logistics systems is important since the users from those systems will make up the majority of ECSS users, but it is also important to use data from analogous systems. The ECSS analysis team collected data from the following analogous systems: DEAMS, Navy ERP, GCSS-AF, NIPRNET, ESD, and two large private

companies (company 1 and company 2). Table 9 lists the systems with their associated acronyms and descriptions:

Table 9 ECSS Analogous System Details

System	Acronym	Description
Defense Enterprise Accounting and Management System	DEAMS	DEAMS is a financial management initiative designed to transform business and financial management processes and systems to provide accurate, reliable, and timely business information to support effective business decision making for U.S. Transportation Command, Defense Finance and Accounting Service (DFAS), the U.S. Air Force and eventually, other agencies within the Department of Defense <https://acc.dau.mil/CommunityBrowser.aspx?id=32306>.
Navy Enterprise Resource Planning System	Navy ERP	Navy ERP is an integrated business management system that updates and standardizes Navy business operations, provides financial transparency and total asset visibility across the enterprise, and increases effectiveness and efficiency <http://www.erp.navy.mil/about_erp.html>.
Business Systems Modernization	BSM	BSM is the Defense Logistics Agency's ERP systems. Similar to other DoD efforts, BSM will be comprised of COTS systems and will streamline the flow of information <http://www.dla.mil/j-6/bsm/default.asp?page=COM>.
Global Combat Support System - Air Force	GCSS-AF	GCSS-AF has revolutionized Air Force operations by integrating 400 applications and data from finance, logistics and personnel systems into one enterprise <http://www.lockheedmartin.com/products/gcss-af/index.html>.
Non-Classified Internet Protocal Router Network	NIPRNET	The NIPRNet is a global long-haul IP based network to support unclassified IP data communications services for combat support applications to the Department of Defense (DoD), Joint Chiefs of Staff (JS), Military Departments (MILDEPS), and Combatant Commands (COCOM) <http://www.disa.mil/services/data.html>.
Enterprise Service Desk	ESD	ESD provides overarching Service Desk as well as Tier 1, 2, and 3 service management of IT systems. It provides a single point of contact, to all Army Enterprise network users, for technical and operational support on all Army Enterprise applications, computing environments and transport means <http://architecture.army.mil/technical-view/enterprise-service-desk.html>.
Company 1		Company 1 is a Fortune 500 company that specializes in the poduction and management of raw materials.
Company 2		Company 2 is a Fortune 500 company that specalizes in technology and media.

Except for the NIPRNET, all the systems listed in Table 9 use commercial IT solutions to facilitate the flow of information through multiple organizations.

DEAMS provided the amount of Help Desk FTEs utilized for level I and II. Although not useful for predicting arrivals and service rates since calculations would require several assumptions like constant service levels between all the companies, this study will compare average FTEs for DEAMs with the results of this estimate.

The level II data received from analogous systems is limited. The Navy's ERP system provided the percentage and totals of level I, II, and III calls received in two sets. The Navy ERP also showed the total number of help desk FTEs and system users. GCSS provides the number of calls per user rate and the percentage of calls to level II broken out by year and month from October 2004 to April 2010. The NIPRNET study presents the number of calls per user rate with a high and low observation. The NIPRNET study also shows the number of total users and total help desk FTEs. ESD provided total tickets created, assigned, routed, fixed, and technicians per day. The ESD data is unique because technicians respond to phone and email help desk tickets making them a contact center. The ESD data is also skewed because the top five technicians out of the total 66 close 39% of the total tickets; therefore, the study will not use ESD data to calculate the service rate for ECSS. Company 1 provided the number of calls per user per month, the level II total FTEs, total number of system users, and average help desk tickets by level I and II. Finally, company 2 provided the total number of help desk tickets per year broken out by level I and II and total level I and II FTEs.

The major limitation of this study is the data. Without a dataset for level I and II help desks, the study cannot test assumptions with arrival rate, service rate, patience, and the distributions of these metrics. With the limited data for call center operations especially for level II, this study will use the best estimates but will focus on presenting an accurate model that analysts can use to update constantly changing values. Table 10 provides an overview of the data received for this study.

Table 10: Data Summary

Source	Total Users	Level 1 FTE	Level 1 User/FTE	Level 2 FTE	Level 2 User/FTE	Calls per User per Month	Equivalent ECSS Calls/Day	Level 1 Minuts per Call	Level 2 Minuts Per Call
PMO Estimate	40,000	16.1	2,484	16.4	2,439.0	1.35	1775	7.50	11.5
AFCAA Estimate	40,000	11.8	3,390	14.3	2,797.2				
AFLMA Estimate	40,000	21.9	1,826	23.5	1,702.1	1.6	2104	4.00	12
5th MRS Estimate	40,000			16	2,500.0	1.1	1447		11.5
Legacy Systems	273,111	3.9	70,028	1.5	182,074.0	0.47	618	18.55	17.74
DEAMS	27,214	14.5	1,877	12	2,267.8				
Navy ERP	66,000	30	2,200	52	1,269.2	0.16	210		
GCSS	834,172					0.018	24		
NIPRENT Study	750,000	1128	665			1.1	1447	5.85	
ESD	750,000	627	1,196						
Company 1	30,000	80	375	100	300.0	2.2	2893		
Company 2	20,000			120	166.7				

Calculations and Estimations

In order to use the queueing models and run simulations for the call center, this study must determine the arrival rates, service rates, and customer patience to use from the collected data presented earlier in this chapter. This study selected a set of values to represent a middle, high, and low estimate for each variable. From the sets, the analysis will create a design of experiments (DOE) to measure the effects of variance on the model.

Arrival Rate and Call Volume Distribution

A difficult task in this study was to determine the arrival rate and the call volume distribution over a period. The arrival rate was determined from the average calls per user per month. The projected total ECSS users are 40,000 after Release 1. With the projected total users, the analysis can calculate the total calls per month, per day, per hour, and per minute. This study used the Navy ERP average calls per user per month as the light arrival rate. This study calculated the moderate rate of 0.47 through the summation of average calls per month for each legacy system. The high rate came from the AFLMA 2010 estimate. The Table 11 lists the calls per user per hour.

Table 11: Calculated Arrival Rates

	Calls per user per month	Users	Calls per month	Calls per day	Calls per hour
Low	0.16	40,000	6,400	210.41	8.77
Moderate	0.47	40,000	18,800	618.08	25.75
High	1.6	40,000	64,000	2,104.11	87.67

Level II calls are included in Table 11's arrival rate, since Level 1 agents initially service calls and transfer to level 2 agents at an average rate. For the level 2 arrival rate, this analysis used 15.6%, 40%, and 72.4% as the low, middle, and high percentages of calls passed on to level 2 agents. That pass off rate of 15.6% is the lowest observed rate from the ECSS legacy system data; 72.4% is the highest rate in the dataset; and 40% is the pass off goal set by the ECSS PMO.

Determining the daily distribution of calls was the second challenge of this analysis. The data received did not break out mean arrivals by a time interval, so this analysis used the Brown et al. distribution for arrivals. The Brown et al. data comes from a bank's call center operating in Israel for 12 months with about 750,000 calls. This assumption is a topic for future research since researchers have not analyzed the distribution from a bank's call center with an ERP system. Figure 6 presents the initial daily distribution of calls from Brown et al.

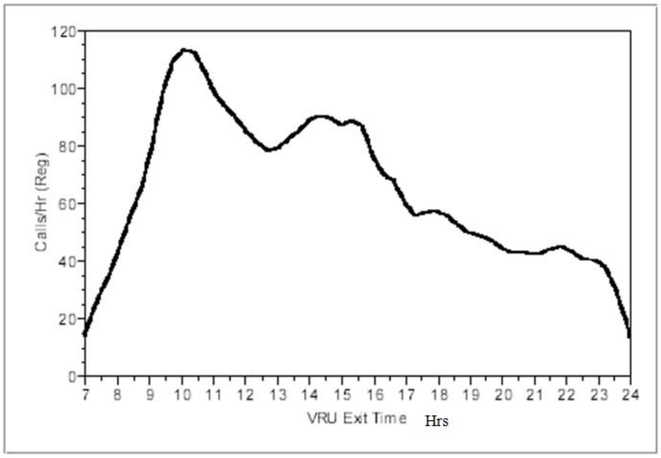


Figure 6: Theoretical Call Distribution (Brown et al., 2002)

The distribution in Figure 6 is based on three types of callers broken out in Figure 7. The NE curve represents new callers, NW represents regular callers, and IN represents Internet Assistance. This study assumes that the bank's customers are similar to the ECSS users since the majority of both classes work during the daytime and call the help desk seeking service and assistance. The peak times for calls intuitively make sense since the arrivals increase peak at around 10:30 am, a dip during the lunch period is observed, and a final peak at around 3pm is followed by a steady decline until a new workday begins. The only stretch is to include the IN callers since their distribution is heavier later at night representing customers accessing the bank's website after work during personal time. This study created an approximate cumulative distribution with the NE and NW distributions listed in Figure 7.

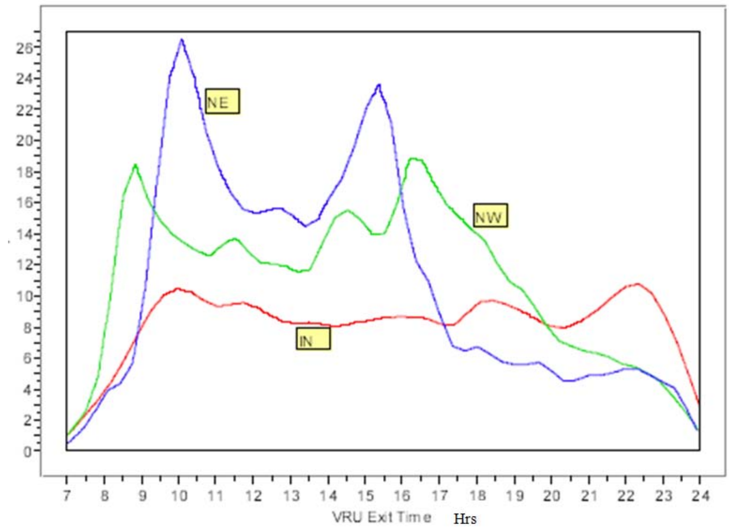


Figure 7: Bank Call Distribution By Type **(Brown L. N., 2002)**

Figure 8 shows the cumulative distribution of the NE and NW calls from Brown et al. This study used this distribution as a theoretical distribution for all callers in a time zone. Figure 8 shows relatively low call volumes from midnight until about 7 AM. The peaks are at about 10 AM and 3 PM, which is logical since people have settled into their tasks for the day by 10 AM, and at 3 PM they have completed lunch and are gearing up to finish the day.

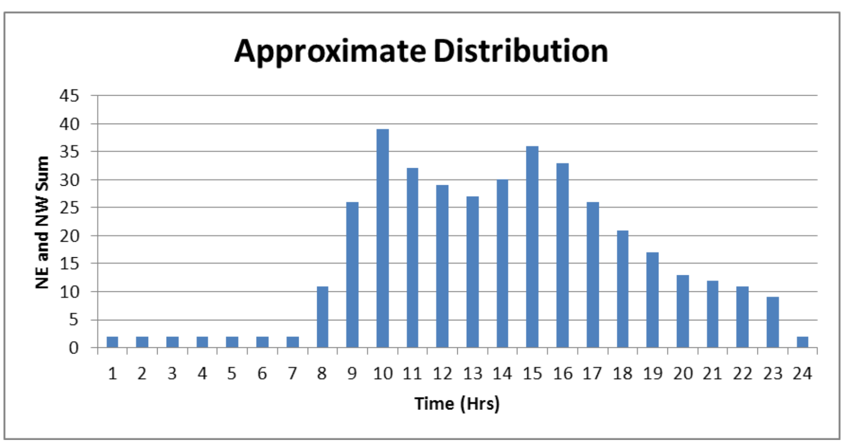


Figure 8: Approximate Call Arrival Distribution

The distribution depicted in Figure 8 does not capture the full ECSS customer population. Since the time zones of each user are unknown, the number of bases in each time zone was used to weight the distributions for Eastern, Central, Mountain, and Pacific

Time zones. Figure 9 shows the continental US (CONUS) distribution converted to percentage of calls and time in Eastern Standard Time (EST).

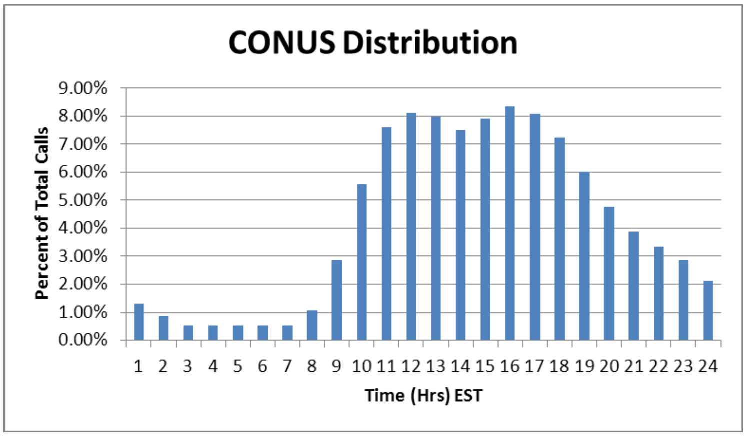


Figure 9: CONUS Call Arrival Distribution (EST)

The final modification to the time zone was to incorporate PACAF and USAFE, the Air Force's commands in Asia and Europe. The cities used for PACAF and USAFE were Tokyo and Prague. The percentages of users in CONUS are 90%, 6% for PACAF, and 4% for USAFE. Figure 10 shows the final distribution of calls for ECSS.

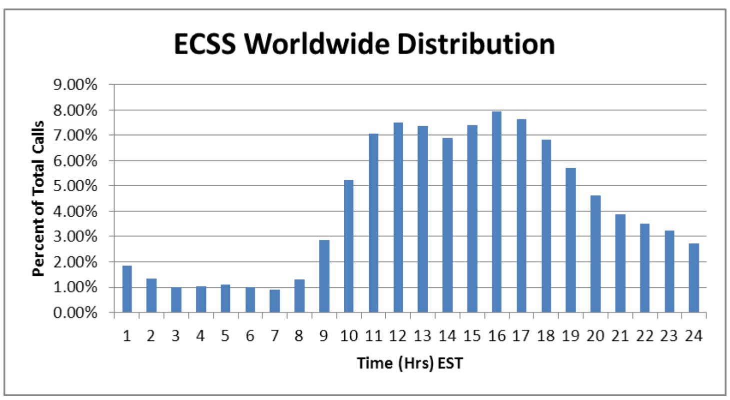


Figure 10: ECSS Call Arrival Distribution (EST)

The next progression from the daily distribution would be to estimate an annual distribution capturing seasonal trends such as fiscal year closeout and training exercises. Unfortunately, the Air Force determined the data to forecast annual call distributions for

the ECSS legacy systems classified since it would show call spikes correlated with classified annual operations and exercises.

Service Rates and Agents

The high, middle, and low Level 1 and 2 service rates used for this study came from the FAS 2010 legacy systems data, the ECSS PMO estimate, and AFLMA estimate. A challenge with using the average service rates from the 2010 legacy system data is that each system has different service agreements with the FAS, so the types of service are not uniform among the systems. Table 12 shows the mean service rates used in this study.

Table 12: Mean Service Rates

	Level 1 Minutes per call	Level 1 Served per Hour	Level 2 Minutes per call	Level 2 Served per Hour
High	4.00	15.00	11.50	5.22
Mid	7.50	8.00	12.00	5.00
Low	18.55	3.23	17.74	3.38

The analysis used the AFLMA Level 1 service rate as the high value; the ECSS PMO estimate as the middle value; and the ECSS FY10 legacy system average rate as the low value (low number served per hour).

This study uses the Square Root Safety Staffing Rule, presented through Equation 1, to determine the appropriate staffing requirements for the call center. For the square-root-rule, as beta approaches zero, the number of agents required becomes the ratio of the arrival and service rate. Increasing beta represents an increased safety factor for variability. The challenge is to determine the appropriate beta while staying within the constraints of budget and resources. This study uses beta values of 0.7, 0.4, and 0.1 to test staffing requirements for each time interval.

The varying arrival rate and constraints with shift schedules makes it difficult to determine the appropriate staffing levels that match the arrival rates. The Square Root Safety Staffing Rule is used to calculate the required number of agents for each hour, but a call center servicing a call distribution similar to Figure 10 would not operate efficiently due to the inability to service peak and low arrivals. In order to answer solve this problem, the number of agents to assign to each shift must be determined through an optimization with the Solver Excel add-in. The analysis used six shifts to solve this problem. The first three shifts covered a 24-hour period from 1 AM to 8 AM, 9 AM to 4 PM, and 5 PM to 12 AM. To supplement the three core shifts and enable flexibility for peaks and lows, the analysis uses three booster shifts covering 10 AM to 5 PM, 11 AM to 6 PM, and 4 PM to 11 PM. .

The objective function of the optimization is to minimize the number of agents, and the number of agents is the sum of total agents per shift. The following represents the decision variables, objective function, and constraints:

Decision Variables:

A_i = number of agents assigned in the hour; i=1, … , 24

Objective Function:

Minimize:

Subject to:

$$1A_1+1A_2+1A_3+1A_4+1A_5+1A_6+1A_7+1A_8+0A_9+\ldots+0A_{24}$$

$$0A_1+\ldots+0A_8+1A_9+1A_{10}+1A_{11}+1A_{12}+1A_{13}+1A_{14}+1A_{15}+1A_{16}+0A_{17}+\ldots+0A_{24} =$$

$$0A_1+\ldots+0A_{16}+1A_{17}+1A_{18}+1A_{19}+1A_{20}+1A_{21}+1A_{22}+1A_{23}+1A_{24}$$

$$0A_1+\ldots+0A_9+1A_{10}+1A_{11}+1A_{12}+1A_{13}+1A_{14}+1A_{15}+1A_{16}+1A_{17}+0A_{18}+\ldots+0A_{24}$$

$$0A_1 + \ldots + 0A_{15} + 1A_{16} + 1A_{17} + 1A_{18} + 1A_{19} + 1A_{20} + 1A_{21} + 1A_{22} + 1A_{23} + 0A_{24}$$

$$0A_1 + \ldots + 0A_{10} + 1A_{11} + 1A_{12} + 1A_{13} + 1A_{14} + 1A_{15} + 1A_{16} + 1A_{17} + 1A_{18} + 0A_{19} + \ldots + 0A_{24}$$

$$A_i \quad ; i=1, \ldots , 24$$

A_i R_i i=1, … , 24, where R_i = Number of agents required in the hour; i=1, … , 24

All A_i must be integers

The optimization used binary coefficients to indicate the hours that fell under each shift. The total workers scheduled by shift are the product of each binary variable with the number of agents used. The number of workers scheduled must be an integer. The ECSS help desk will not utilize part-time agents, so all shifts must be 8 hours and partial agents are not used.

Customer Patience

A customer's patience determines their desire to wait in line or eventually abandon their place in the queue. This action is also known as reneging. A limitation with this study is the lack of abandonment data collected. The FAS provided the percentage of total callers that abandoned before receiving service, but did not track abandonment mean times, standard deviations, or distributions. This study uses theoretical mean times before a caller reneges. This study used the customers in the Brown et al. study as the low mean time before a customer reneges. This assumption allows this research to use mean abandonment times from Table 8. The average wait time before abandoning in Table 8 is approximately 95 seconds or 1.58 minutes. The FAS reported ASA times of about 4 minutes, so this will be used as the mid-value. Finally, this research used a high mean time of 8 minutes to test the impact of very patient callers. A follow-up study should collect data to validate these metrics.

Table 13: Mean Time Before Renege

	Renege Time (Minutes)
High	1.58
Mid	4
Low	8.00

Queueing Models

This study analyzed two queueing models to forecast call center metrics. The first model is the Erlang C model presented in Chapter 2 of this thesis. The second model is the Erlang A model, also known as the Palm model, to account for abandonment. This section will discuss the performance measure calculations for the Erlang A model. The approximations listed in the study by Garnett et al. are:

- The probability of waiting P{W>0}
- The probability of abandoning given the customer waits P{Ab|W>0}
- The probability that a customer entering the system abandons P{Ab}
- The expected time a customer entering the system will wait E[W]
- The expected number of busy agents E[#busy agents]
- The expected number of customers waiting in the queue E[#waiting in queue].

These measures are calculated through the hazard rate function h(x) and waiting (ω), which is a relationship between potential waiting time and patience. The hazard rate function is the standard normal density function φ(x) divided by the difference of one and the distribution function Φ(x) (Garnett et al., 2002).

Normal Density Function:

Distribution Function:

Hazard Function:

Waiting Function:

The derived approximations for the Erlang A performance measures are very accurate for high volume call centers with patient customers. As customer patience approaches infinity, the formulas will match the output of the Erlang C performance measures, which do not take into account patience. For ECSS, analysts do not project the help desk to be large and the level II help desk will be even smaller. For the Erlang A model, the formulas are approximations with increasing variance from simulated data as customer patience decreases. The increasing inaccuracy of the formulas as patience decreases is the downside of using this approach. Due to the limitations of the Erlang A derived approximations; this study will use simulation to model abandonment in the ECSS help desk.

Simulation

Subject matter experts at the FAS confirmed that call center simulation is underutilized in the Air Force. The standard for call center estimation is statistical analysis, but for a new complex system like ECSS with a limited dataset, simulation is a viable alternative. Simulation allows analysts to test multiple combinations of inputs and capture unique system behaviors. This study uses the ARENA simulation package to create the model and simulate the operations of the call center. This study presents three models to measure the variability of their results: M/M/S (Erlang C) with fixed arrival, M/M/S (Erlang C) with time dependent arrivals, and M/M/S + M (Erlang A) with time

dependent arrivals. The following section will show the models used and the logic with each function.

Model

The first model created represents a simple M/M/S model. The call created module generates customers calling the help desk with an exponential distribution. Once the user places the call, they enter the VRU where the system prompts them to select from a list of options to direct them to the correct set of agents. The VRU delays customers with low, middle, and high values of 10, 15, and 30 seconds provided by a FAS subject matter expert. The triangular distribution was selected due to the lack of data to fit a statistical distribution. Figure 11 lists the M/M/S model.

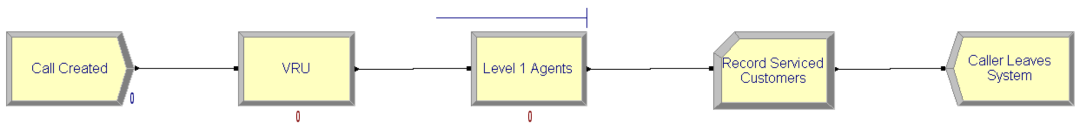


Figure 11: M/M/S Model

Once the system routes the caller to the correct service, the Level 1 Agent process module seizes the entities and provides service. If all agents are occupied, the callers will wait in a virtual queue until they reach an agent. Once complete, the customers leave the server, the record module tallies the entity, and the entity is disposed.

The second variation of this model incorporates varying arrival rates based on the estimated worldwide ECSS distribution and varying customer service agents to match the demand. Figure 12 shows an example of the mean time between arrivals (MTBA) coded in ARENA. ARENA uses MTBA as the input for arrivals versus an average total number of arrivals over a period. Figure 12 is the conversion of mean arrivals by hour to the MTBA by hour.

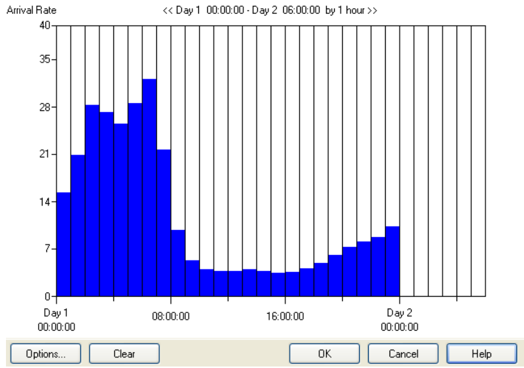


Figure 12: Varying Arrival Rate Example

The final ARENA model created is the M/M/S+M model, which captures customers abandoning the system after a certain time waiting in the queue. Figure 13 shows the model.

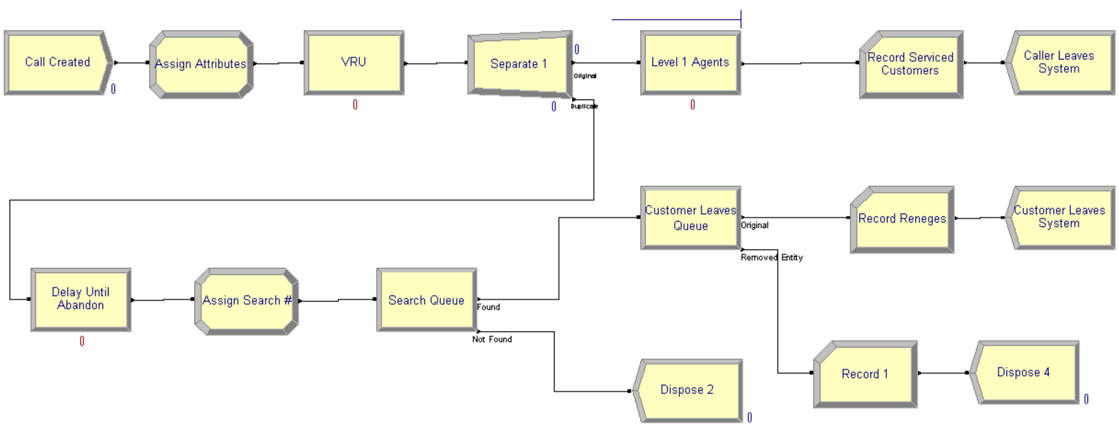


Figure 13: M/M/S+M Model

The Assign module assigns a unique number for each entity created to allow the Search Queue function to search for the entity in the queue. The Assign module also assigns a renege time to the entity from an exponential distribution. This captures the randomness of a customer's patience. The Separate module creates an exact duplicate of the entity with attributes before it enters the Level 1 Agent process. The duplicate entity is routed to the Delay Until Abandon process, where the duplicate waits until the assigned renege time has passed.

After the time has passed, a new variable is assigned, and the search process begins. If the customer is still in the queue, then the customer has waited past the threshold of their patience and they are removed from the queue. The remaining blocks dispose of the duplicate and the caller if found. The varying arrival rates and number of call center agents remain the same from the previous M/M/S model. A detailed explanation of the call center model with reneging can be found in chapter 8 of the book *Simulation With Arena* (Kelton et al., 2002).

Experiment Design

The simulation will provide outputs that are dependent on the parameters entered into the model. In order to test the relationships between dependent and independent variables, this study designed an initial pilot study that tests all possible combinations of the following help desk scenarios listed in Table 14.

Table 14: Design of Experiments: Pilot Study

		Total Daily Calls			Service Rate (Minutes)			Renege Time (Minutes)		
Staffing Regimes	Agents	Low	Mid	High	Low	Mid	High	Low	Mid	High
Light Arrival, Low Service Rate	12	100	210	565	4	7.5	18.55	1.58	4	8
Light Arrival, Mid Service Rate	6	100	210	565	4	7.5	18.55	1.58	4	8
Light Arrival, High Service Rate	4	100	210	565	4	7.5	18.55	1.58	4	8
Moderate Arrival, Low Service Rate	31	210	618	1775	4	7.5	18.55	1.58	4	8
Moderate Arrival, Mid Service Rate	14	210	618	1775	4	7.5	18.55	1.58	4	8
Moderate Arrival, High Service Rate	8	210	618	1775	4	7.5	18.55	1.58	4	8
High Arrival, Low Service Rate	101	1775	2104	2893	4	7.5	18.55	1.58	4	8
High Arrival, Mid Service Rate	43	1775	2104	2893	4	7.5	18.55	1.58	4	8
Heavy Arrival, High Service Rate	23	1775	2104	2893	4	7.5	18.55	1.58	4	8

The experiment yields 243 unique scenarios, and each scenario ran for 183 days with three repetitions to get a general sense of the model's performance. The 243 staffing level, call volume, and service rate combinations resulted in a wide range of metrics. The pilot study allowed the analysis to filter out the staffing levels that provided unacceptable metrics for service time, utilization, and renege percentages.

The study ran a second pilot simulation on the remaining staffing regimes for projected Level 1 and 2 help desk estimates with longer runtimes. Table 15 shows the low, middle, and high values used as inputs for the Level 1 and 2 simulations. The Level 2 call volumes were calculated by using the 40% metric set by the ECSS PMO. This study assumed that the customer's patience would remain the same when transferred to the Level 2 help desk. The study used the Level 2 legacy system data for the service rate. This analysis assumed longer average service rates for Level 2 support since the issues are generally more complex than Level 1 issues.

Table 15: Level 1 and 2 Simulations

Help Desk Level	Total Daily Calls			Service Rate (Minutes)	Renege Time (Minutes)
	Low	Mid	High		
Level 1	210	618	1775	7.5	4
Level 2	84	247	710	17.74	4

The thesis analyzed the results from the second pilot simulation to show the tradeoffs between staffing levels and help desk performance. The simulations conclude with an analysis of variance and sensitivity analysis of the selected staffing levels for projected call volumes.

Simulation Parameters

The study simulated the optimal staffing levels with 20 repetitions to determine a confidence interval. The required sample size was calculated through the sample size determination formula discussed by McClave et al (McClave et al., 2008). Formula 2 represents the calculation for required sample size based on the desired alpha.

Formula 2:

Formula 2 uses sampling error, Z scores, and population standard deviation to calculate the required sample size based on a designated confidence interval. To use Formula 2, this study simulated a scenario with 14 agents, 618 mean daily calls, 7.5 minutes mean service rate, and 4 minute mean renege time for 30 repetitions. By assuming that the standard deviation of the 30 repetitions represents the population, the study was able to use the standard deviation from this simulation in Formula 2.

The final analysis before creating the simulation for the selected scenarios was to test the appropriate run duration for the iterations of the model. The test used the same scenario from the previous chapter and varied the duration from 5 days to 8,760 days to test the impact of simulation duration with wait time. The test revealed that the response changed as the duration increased up to around 2,190 days where the values begin to stabilize. The simulations used 2372.5 days as the duration to minimize the variability created with shorter runtimes. The selected duration is a balance between accuracy and minimizing the time each simulation took to run, since a longer duration increases the time it takes to simulate a scenario. Figure 14 and 15 show the results of the test.

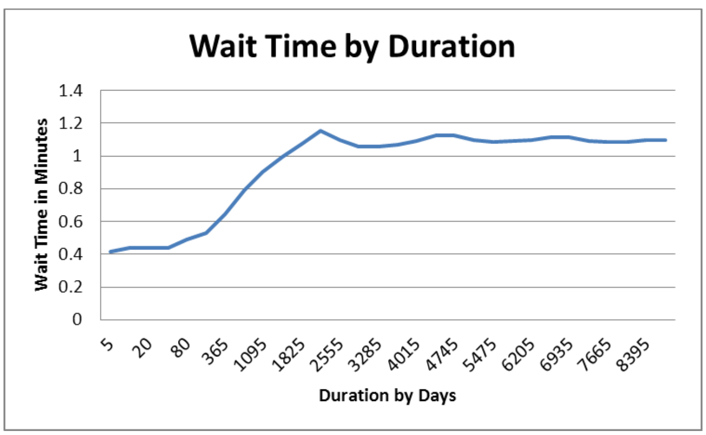


Figure 14: Duration Test Results (Wait Time)

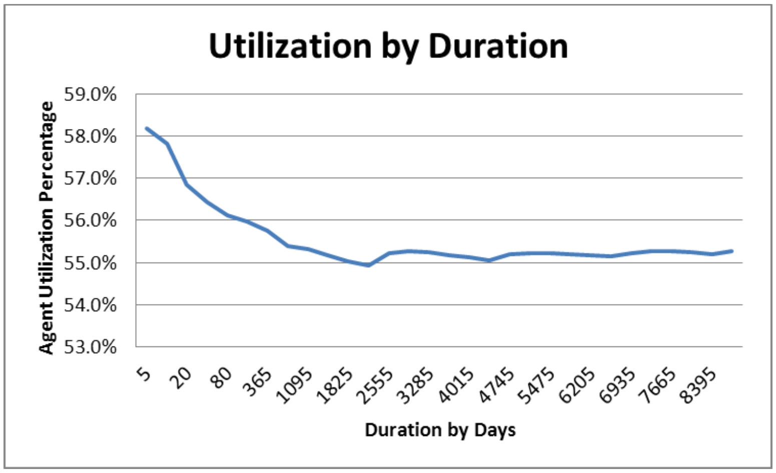


Figure 15: Duration Test Results (Utilization)

Prior Estimates

Forecasting the manning requirements for the ECSS help desk is an important topic that has been the subject of several estimates. This section will discuss the results of the prior studies and will show how this research will incorporate their findings. To date, there are four FTE estimates for ECSS: the ECSS program management office (PMO), the Air Force Cost Analysis Agency (AFCAA), the Air Force Logistics Management Agency (AFLMA), and the fifth Manpower Requirements Squadron (5^{th} MRS).

After release 1 for ECSS, the projected user base is 40,000. ECSS PMO estimates 1.35 calls per user per month, which translates to 54,000 calls per month and about 1,775 calls per day. They estimated that 40% of the calls would pass to level II, so the PMO estimated 16.1 and 16.4 FTEs for level I and II respectfully. The AFCAA took a different approach and used three ratios for help desk FTEs to users. Table 16 shows the rates:

Table 16 AFCAA FTE to User Ratios

Helpdesk FTEs	Initial Deployment	Medium Term	Long Term
Tier 1 Help Desk	1/2,200 Users	1/2,800 Users	1/3,400 Users
Tier 2 Help Desk	1/1,300 Users	1/1,900 Users	1/2,800 Users

Their estimate resulted in:

- 17.4 level I FTEs and 30.8 level II FTEs for initial deployment
- 14.3 level I FTEs and 21.1 level II FTEs for medium term
- 11.8 level I FTEs and 14.3 level II FTEs for long term steady state

The AFCAA accounted for an initial peak in workload once release 1 has commenced. Long term, the AFCAA estimates less required FTEs than the PMO.

The next estimate is the AFLMA estimate in April 2010. Similar to the ECSS PMO, the AFLMA used a per-user per-month call rate. Their rate was slightly higher at 1.6 contacts per month per user, but their FTE estimates were significantly higher. The AFLMA accounted for agent utilization rates in their estimate and used average call lengths of 4 and 12 minutes for level I and II. Finally, the AFLMA used the projected total daily calls by the total amount of calls that a help desk FTE can handle to determine the required FTEs. The AFLMA estimate came out to 21.9 and 23.47 level I and II FTEs required

Finally, the 5th MRS estimated the level II FTE requirement by using manpower factors along with the per user and per month contact rate. They conducted a matrix analysis by varying contacts per user (1.1, 3.3, and 6.6) and agent utilization rates (25%, 30%, and 44%). Their analysis came out to:

- 23 FTEs at 1.1 contacts per user per month
- 69 FTEs at 3.3 contacts per user

- 138 FTEs at 6.6 contacts per user.

There is a wide range of estimates for the required ECSS help desk FTEs. Level I estimates ranges from 11.8 FTEs up to 21.9 FTEs and level II ranges from 14.3 FTEs to 138 FTEs. This analysis will simulate several different scenarios and will incorporate utilization rates, abandonment, and varying traffic loads.

Chapter Summary

Chapter 3 presented the methods used to answer the research questions addressed in Chapter 1. The report uses data from legacy and analogous systems to simulate the performance metrics for the ECSS help desk. The simulation will account for utilization rates, abandonment, and varying traffic loads. The study will compare results from the Erlang C equations and the Erlang C simulation with the Erlang A simulation. Finally, the study will compare the FTE estimate with prior estimates for the ECSS help desk. Figure 16 presents the summary of the analysis tools used in this study.

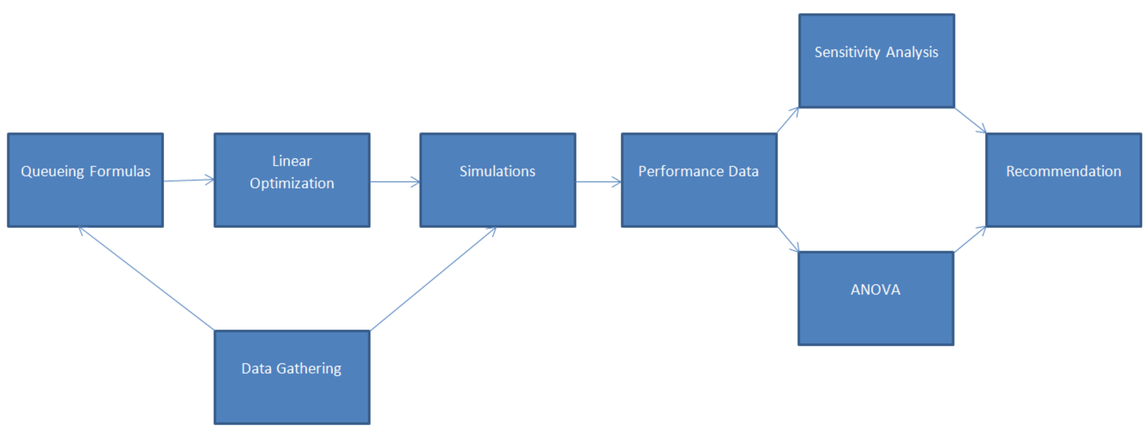


Figure 16: Methodology Summary

IV: Results and Analysis

Overview

This research adds a unique staffing estimate for the ECSS help desk. Queueing theory, linear optimization, simulation, and statistical analysis were required in order to determine the appropriate FTE requirements and analyze the sensitivity of each variable's impact. Through the findings of this study, recommendations can be made regarding performance trade-offs with staffing levels. This chapter presents the results of the research methodology discussed in Chapter 3. The first section will discuss the results of the required FTEs of the nine staffing regimes. The next section will present key findings through the Erlang C and Erlang A model analysis. The third section will discuss the statistical analysis of the simulation model outputs. Finally, the chapter will conclude with a summary.

Required Full Time Equivalents

Determining the required FTEs for varying daily call volumes and varying service rates required a multi-step process. The first step was to determine the mean percentage of calls for each hour block in a 24-hour day. This study used the distribution from Brown et al.'s study of the bank call center to create the ECSS worldwide daily distribution of calls. Table 17 shows the percentage of daily calls arriving at each hour. With the distribution of calls defined as a percentage of total daily calls, this study was able to break out all calls per day estimates by hour.

Table 17: Percentage of Calls by Hour

Time (Hours)	Worldwide Total %
1:00 AM	1.84%
2:00 AM	1.36%
3:00 AM	1.01%
4:00 AM	1.04%
5:00 AM	1.11%
6:00 AM	0.99%
7:00 AM	0.89%
8:00 AM	1.31%
9:00 AM	2.87%
10:00 AM	5.25%
11:00 AM	7.05%
12:00 PM	7.49%
1:00 PM	7.35%
2:00 PM	6.88%
3:00 PM	7.41%
4:00 PM	7.96%
5:00 PM	7.63%
6:00 PM	6.84%
7:00 PM	5.71%
8:00 PM	4.64%
9:00 PM	3.89%
10:00 PM	3.50%
11:00 PM	3.24%
12:00 AM	2.74%
	100.00%

In order to incorporate the call distribution into ARENA, this study converted the arrival rate to MTBA in minutes by dividing 60 by the calls per hour. Appendix D shows the calls per hour and MTBA for several daily call scenarios.

The next step was to apply the Square Root Safety Staffing Rule, represented by Formula 1 from Chapter 2, to determine the staffing requirements based on the designated beta safety factor. For this study, the initial calculations used a beta of 0.1. Appendix E lists the results of these calculations. The results show that noon and 4pm require the most agents.

Table 18: Agents Required by Arrivals and Service Rate

Total Daily Arrivals	Mean Service rate (Min)
618.08	7.50

Hr	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	11.38	8.00	1.42	0.1	1.54	2
2	8.38	8.00	1.05	0.1	1.15	2
3	6.21	8.00	0.78	0.1	0.86	1
4	6.44	8.00	0.80	0.1	0.89	1
5	6.88	8.00	0.86	0.1	0.95	1
6	6.15	8.00	0.77	0.1	0.86	1
7	5.48	8.00	0.68	0.1	0.77	1
8	8.07	8.00	1.01	0.1	1.11	2
9	17.73	8.00	2.22	0.1	2.36	3
10	32.43	8.00	4.05	0.1	4.26	5
11	43.60	8.00	5.45	0.1	5.68	6
12	46.31	8.00	5.79	0.1	6.03	7
13	45.43	8.00	5.68	0.1	5.92	6
14	42.54	8.00	5.32	0.1	5.55	6
15	45.81	8.00	5.73	0.1	5.97	6
16	49.17	8.00	6.15	0.1	6.39	7
17	47.15	8.00	5.89	0.1	6.14	7
18	42.25	8.00	5.28	0.1	5.51	6
19	35.30	8.00	4.41	0.1	4.62	5
20	28.66	8.00	3.58	0.1	3.77	4
21	24.06	8.00	3.01	0.1	3.18	4
22	21.66	8.00	2.71	0.1	2.87	3
23	20.05	8.00	2.51	0.1	2.66	3
24	16.94	8.00	2.12	0.1	2.26	3

The last page of Appendix E shows the sensitivity of beta. When the analysis increased beta to 0.3, the manning requirements during the peak hours rose by about one. Similarly, when beta increased to 0.7, the manning requirements during the peak hours rose by about one. To test the influence of beta on the models, the analysis ran the first pilot simulation with varying schedules, arrivals, and service rates in both the Erlang C and Erlang A models. The results show that with a low beta, the Erlang C model could not handle higher ratios of arrival rate and service rate. For example, all the staffing regimes that planned for a low mean service rate and tested with a higher mean service rate failed to complete the simulation due to the software reaching the maximum number of entities. This occurred because calls were entering the system at a rate higher than the system was able to process them. The Erlang A model was capable of handling the higher ratios due to its abandonment property that allowed customers in the system to

leave after they stayed in the queue past their patience level. Longer queues equated to longer wait times, and the longer wait times resulted in higher rates of customers abandoning their place in the queue.

With the number of agents required for each hour in a day, the next step was to determine an optimal schedule to meet the demand. The constraints of this problem are the minimum agent requirements, and 8-hour shifts. Utilizing only three 8-hour shifts is a sub-optimal solution due to the inflexibility to meet higher demands and gear down during slow periods, and having a large number of shifts will over complicate scheduling. In order to minimize the number of agents scheduled while meeting the constraints, 3 booster shifts were added in the linear optimization. Appendix F shows the results of the linear optimization. The results allowed this research to build matching agent schedules in ARENA. Appendix G lists the number of agents scheduled per hour in ARENA. The nine schedules represent the nine different scheduling regimes simulated in this study optimally matched for the predicted load. The simulation tested the performance of these regimes in varying conditions.

Erlang C Results (M/M/S)

This research studied the impacts of the Erlang C queueing models through static calculations and dynamic simulation. Both cases yielded interesting results with strengths and weaknesses of both methods. The formulas analyzed scenarios with steady state variables of fixed arrival rates and fixed service rates. The simulation provided an economical way to study the impact of varying arrival rates without having to make numerous calculations.

This study applied VBA custom functions to calculate the operating characteristics of the Erlang C model with the same scenarios as the simulations except for the number of servers. In these calculations, a server refers to the number of employees required at any given moment. The total number of agents refers to the number of FTEs required to staff the call center for a 24-hour period. Appendix H shows the table of calculations.

With a beta of 0.5, the M/M/S calculations show that at most, only two servers are required to staff a call center with an arrival rate of 3.96 per hour and service rate of about 18.6 minutes per server. In this scenario, agents are busy 61% of the time and customers wait about 11 minutes for service. The strength of this method is that calculations are quick and simple. The downside of this method is the fixed variables, which is why simulation must be incorporated.

The assumed ECSS worldwide hourly distribution of daily calls presented in Figure 10 from Chapter 3 shows a significant range in calls. A mean arrival rate of 3.96 per hour could vary from 7.6 per hour to 0.95 per hour. The variability creates a higher requirement for staffing during these peak times. The simulation could not model certain scenarios due to the imbalance created from the combinations of high arrivals, slow service times, and low staffing. Appendix I lists the results from this simulation.

There are a few key observations from the two datasets. For example, in a scenario where total daily calls are 210 and the average service rate is 18.55 minutes, the simulation with 12 agents yields an agent utilization of 67.7% +/- 0.25% at an alpha of 0.05. The simulation yields a very long average wait time of about 98.6 minutes +/- 2.8

minutes at an alpha of 0.05. The static calculations on the other hand with only 12 agents, yield a utilization of 67.76 percent and average wait time of 5.68 minutes.

Other examples are the high arrivals, long service durations, and low staffing scenarios. In the static calculations, these scenarios yielded utilization rates of up to 61% and wait times as low as 3 minutes. The simulation could not model these scenarios due to the unbalanced rate of arrivals and rate served. It is clear that the introduction of variability changes the model, and variability must be factored into any bottom up help desk analysis.

Erlang A Results (M/M/S + M)

The Erlang C simulation scenarios required a higher safety-staffing beta to increase the number of agents working any given shift, but are the extra agents needed when the study introduces abandonment to the model? The simulation shows that customers abandoning their place in the queue allow help desks to function with lower staffing regimes.

Revisiting the scenario where total daily calls are 210 and the average service rate is 18.55 minutes, the first pilot simulation shows that the 12 agents required to staff this rate for a 24-hour period yields a utilization rate of about 52% +/- 0.04% at an alpha of 0.05. The average wait time was about 1.2 minutes +/- 0.012 minutes at an alpha of 0.05. In this scenario, about 23% of the customers reneged with 4 minutes of patience. The Erlang A simulation shows that lower staffing levels can reasonably service a model with a low or even negative beta value.

The simulation also shows feasibility of operating low-staffed help desks with high arrivals and long service durations. The trade-off with the lower staffing is higher

percentage of customers abandoning their place in the queue. The goal is to optimize the performance metrics while minimizing costs. The next step is to analyze the outputs of the simulation.

This analysis chose the staffing levels with the best performance based on probably daily call totals and service rates to conduct a longer simulation. The longer simulation increased the duration to achieve steady state conditions. The second pilot simulation showed the steady state outputs of the selected staffing levels. Table 19 shows results from the second pilot simulation.

Table 19: Pilot 2 Simulation Results

Scenario	Agents	Rep	Total Daily Calls	Service Rate (min)	Renege Time (min)	Avg Wait Time (sec)	Avg Wait Time 95% C.I.	Agent Utilization	Agent Utilization 95% CI	Renege %	Renege % 95% C.I.
Level 1	23	20	1775	7.5	4	104	0.37	73.4%	0.09%	43.2%	0.16%
Level 1	31	20	1775	7.5	4	69	0.85	66.9%	0.12%	28.7%	0.35%
Level 1	43	20	1775	7.5	4	23	0.50	57.4%	0.03%	9.4%	0.21%
Level 1	8	20	618	7.5	4	112	0.18	68.1%	0.03%	46.7%	0.08%
Level 1	12	20	618	7.5	4	77	1.04	58.8%	0.06%	32.1%	0.44%
Level 1	14	20	618	7.5	4	67	1.28	55.2%	0.08%	27.8%	0.54%
Level 1	6	20	210	7.5	4	73	1.23	43.1%	0.03%	30.3%	0.51%
Level 1	8	20	210	7.5	4	44	1.66	36.6%	0.13%	18.4%	0.69%
Level 2	23	20	710	17.74	4	101	0.32	70.8%	0.07%	42.1%	0.13%
Level 2	31	20	710	17.74	4	68	0.62	63.9%	0.09%	28.5%	0.26%
Level 2	43	20	710	17.74	4	26	0.76	54.5%	0.03%	10.6%	0.32%
Level 2	8	20	247	17.74	4	113	0.30	63.5%	0.05%	46.9%	0.12%
Level 2	12	20	247	17.74	4	80	0.56	54.8%	0.04%	33.1%	0.24%
Level 2	14	20	247	17.74	4	66	0.91	51.6%	0.06%	27.5%	0.38%
Level 2	4	20	84	17.74	4	108	1.05	44.9%	0.06%	44.9%	0.44%
Level 2	6	20	84	17.74	4	76	0.78	38.7%	0.08%	31.6%	0.32%
Level 2	8	20	84	17.74	4	47	1.40	33.2%	0.08%	19.4%	0.58%

Observing the Level 1 scenario with 618 daily calls shows that customers entering a help desk with eight total agents waited 112 seconds, agents were 68% utilized, and about 47% of the callers reneged. By adding four agents, wait times dropped by 34 seconds and renege percentage dropped by 14%, but utilization dropped by 9 %. Adding

an additional 6 agents to the baseline dropped wait times by 46 seconds and renege percentages to 19%, but utilization dropped by 13%.

Statistical Analysis of the Erlang A Model Outputs

Studying the relationships of variables within a study shed light on key decisions such as determining the optimal call center goals. This section discusses the results of the statistical analysis from the simulations. The first section presents the ANOVA of the categorical control variables. Finally, this section discusses the observations between response variables.

ANOVA

The analysis of variance shed light on a few trends. Some trends are obvious, while some surprising. The one-way analysis of wait time and agents in Figure 17 suggest that average wait time and number of agents is negatively related. This observation can also be made with the utilization and percent renege by number of agents in Figures 18 and 19. It appears that adjusting the number of agents might have a significant impact on the performance of the simulation model.

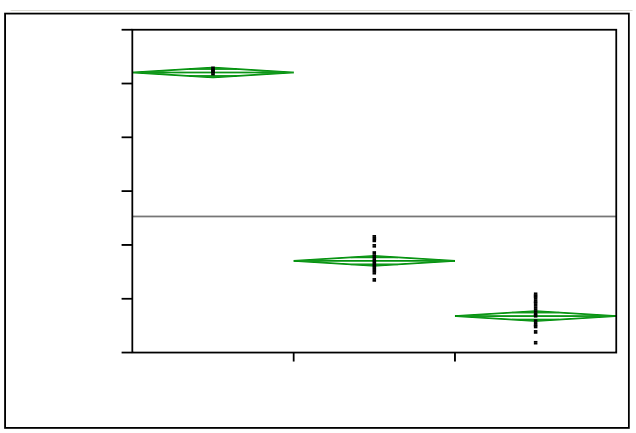


Figure 17: One-way Analysis of Average Wait Time by Agents

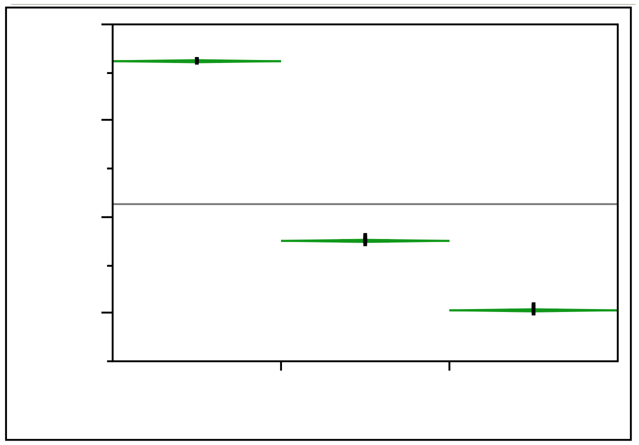


Figure 18: One-way Analysis of Utilization by Agents

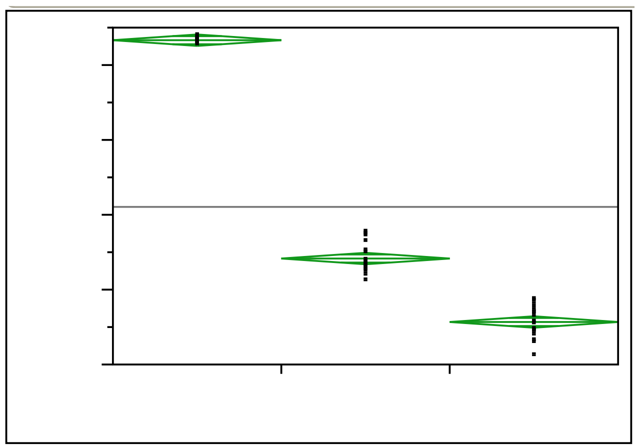


Figure 19: One-way Analysis of Percent Renege by Agents

Response Variable Relationships

Figure 20 shows agent utilization by renege percent from the first pilot simulation. Figure 20 suggests a positive relationship between utilization and percent renege. This relationship makes sense because as agents become busier, customers will have to wait longer for service, which will directly affect the customer's amount of patience while waiting in the queue.

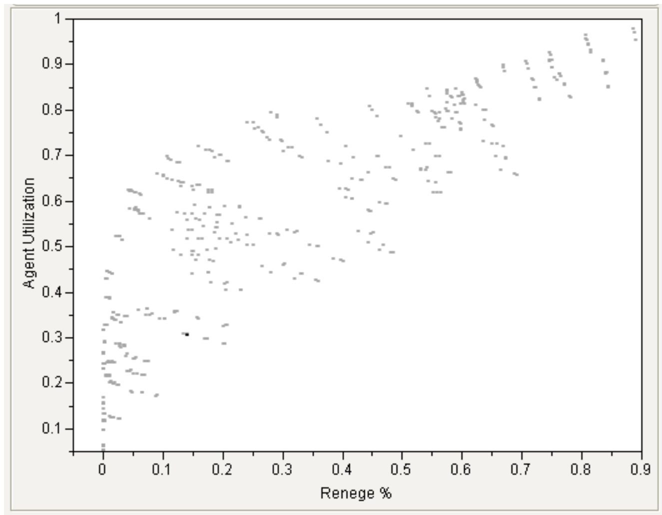


Figure 20: Agent Utilization by Renege Percentage

Figure 21 and 22 show the plot of utilization and renege percentages by wait time. The figures confirm the positive relationships between agent utilization and wait time, and percent renege by wait time. Figure 21 shows three clusters of data points. The three clusters are created by the three staffing levels simulated for the Level 1 help desk with a projected daily call volume of 618.

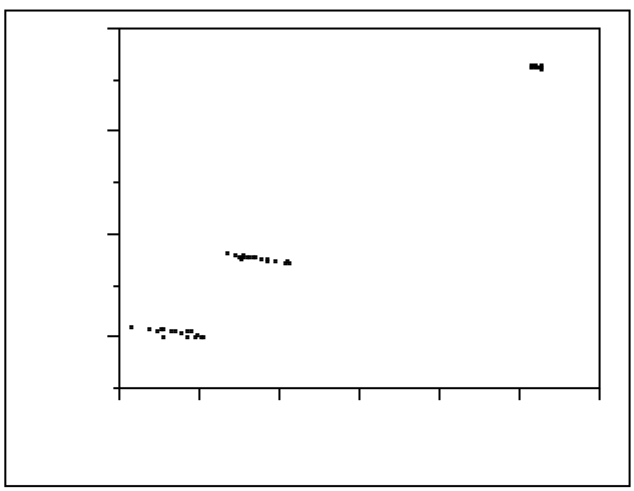


Figure 21 Agent Utilization by Wait Time

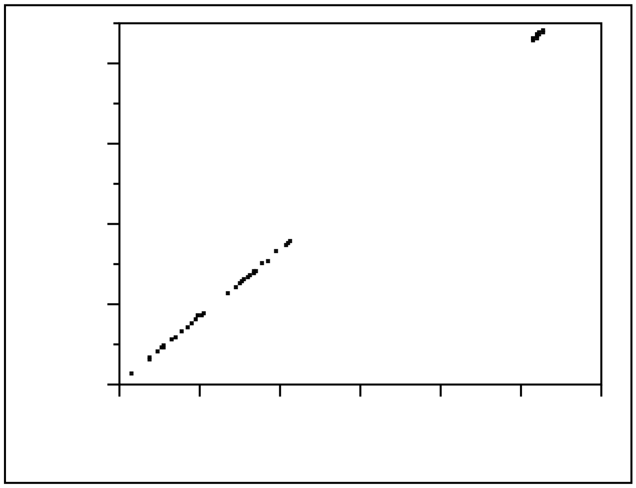


Figure 22: Agent Utilization by Percentage Renege

Diminishing Returns

This study further tested the relationship of adding agents to systems. In this scenario, the help desk experienced 618 calls with a mean service rate of 7.5 minutes and mean renege time of 4 minutes. The Figures 23 and 24 show the marginal diminishing returns on performance as the help desk adds more agents to the system.

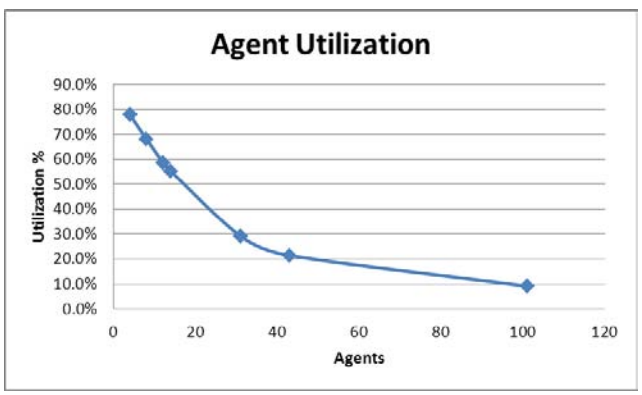


Figure 23: Utilization Marginal Return

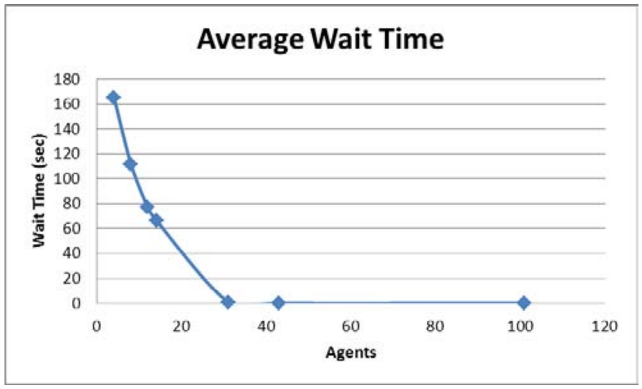


Figure 24: Wait Time Marginal Return

Chapter Summary

In Chapter 4, the study revisited the estimated daily call volume distribution for ECSS from Figure 10. Through the estimate of calls per hour, the study used linear optimization, which efficiently matches agents with shifts to meet user demand. With the input parameters defined, this chapter analyzed the strengths and weaknesses of forecasting with the Erlang C formulas and Erlang C simulation. The study found substantial variance between the two methods. The chapter discussed the Erlang A simulation and the advantages of accounting for abandonment in call center models. The Erlang A simulation showed the flexibility introduced when abandonment is modeled. The chapter provides a means ANOVA of number of agents plotted with average wait time, agent utilization, and renege percentage. The chapter concluded with an analysis of the relationships with average wait time, agent utilization, and renege percentage.

V: Conclusions

Overview

This study's main goal is to assist the implementation of the Expeditionary Combat Support System, the Air Force's largest ERP implementation. The ECSS program management team suggested a further analysis of their help desk estimates. Initial findings showed that the majority of estimates were top-down estimates using general ratios of call center agents per user. This study used a quantitative bottom-up approach through queueing theory, linear optimization, and simulation to determine the appropriate staffing strategy for the possible scenarios.

The final chapter will revisit the research questions and present the findings and recommendations from this study for the ECSS help desk. This will be followed up with, a comparison of the recommended staffing strategy with the prior estimates. Analysis of the sensitivity analysis of the recommended staffing strategy will be presented. The next section will discuss the limitations of the study. Finally, the chapter will conclude with final thoughts and future research opportunities.

Research Questions

1. What is the most probable call volume for ECSS?
2. What are the probable staffing levels to match the projected call volume?
3. What are the optimal trade-offs between service quality and cost savings?

Probable Call Volumes

Throughout the lifecycle of ECSS, the Level 1 help desk might expect between 210 to 1775 calls per day. Call volumes could be as low as 210 calls per day during long-run states where most users are very familiar with the systems. Call volumes could also

reach 1775 calls per day in scenarios like major releases, upgrades, and increased operations tempo where users need a high volume of support. At steady state after the initial spike in help desk demand, the Level 1 can expect about 618 daily calls.

In essence, the Level 2 help desk will experience similar environments like the Level 1 help desk. The major differences are volume and service rate. The Level 2 help desk could see lower call volumes since only about 40% of Level 1 calls are passed to Level 2; and the Level 2 help desk will have a longer average service rate since Level 2 issues are usually more complicated. The Level 2 call volume could range from 84 to 710 calls per month, with a steady state average of 247 daily calls.

Probable Level 1 and 2 Staffing Levels

The staffing levels are dependent on the state of the system. At initial release, the Level 1 call volume could reach 1775 calls per day. That is about 1.1 calls per user per month, which represents the workload once the Air Force releases ECSS to the 40,000 users. The optimal level for this workload is about 31 agents to operate the entire 24 hour period. At this level of staffing, users might wait for an average of 69 seconds +/- 0.85 seconds at an alpha of 0.05and choose to renege 29% of the time +/- 0.35% at an alpha of 0.05. In order to improve performance, the help desk can add more agents at the FAS average contract annual rate of $92,889 (BY10) per agent. For example, by adding 12 more agents, the average wait time will decrease by an average of 46 seconds per call. This equates to a daily savings of 1,361 total minutes at a cost of about $3,054 (BY10) per day or $134.64 per hour.

At steady state, the Level 1 help desk might see about 618 calls per day. That is about 0.47 calls per user per month. At this volume, the optimal staffing level is about 12

agents. At this level of staffing, users might wait for an average of 78 seconds and renege 33% of the time. By adding two additional agents, the average wait time will decrease by an average of 12 seconds per call. This equates to a daily savings of 124 total minutes at a cost of about $509 per day or $246.29 per hour. The increased performance from adding more agents in this scenario does not seem to outweigh the costs associated. An alternative to improve performance is to decrease service times through training and technology.

Finally, at the long-run state, the Level 1 help desk might receive 210 calls per day. At this volume, about 8 agents are sufficient to meet demand. Users will wait an average of 44 seconds +/- 1.66 seconds at an alpha of 0.05and renege 18% of the time +/- 0.69% at an alpha of 0.05. If the ECSS reduced total agents by two, wait times would increase on average 29 seconds and 12% more users would renege. This estimate is similar to the AFCAA estimate, which calculates 11.8 FTE.

The Level 2 estimates for initial, steady state, and long run scenarios are 31, 12, and 8 FTE. The performance of these staffing levels is similar to the Level 1 states since the increased service rate counters the lower call volumes. This study assumes that the major difference between the two levels is that Level 2 agents are at a higher grade and therefore priced at a FAS contract rate of $100,902 (BY10) per agent.

Service Quality and Cost Savings Trade-Offs

There is a positive relationship with adding agents and improving call center performance. A diminishing marginal benefit exists as managers add more agents to the system. The greatest gains in call center metrics occur when agents are added to an understaffed system. This study recommends that the ECSS leadership determine

realistic performance goals for the ECSS help desk. These goals will allow the analysts to fine-tune the calculations in order to estimate required staffing levels.

Another trade-off to consider is whether to establish the help desk for initial, steady state, or long-run states. If the ECSS PMO decides to staff a Level 1 and 2 help desk with 31 and 12 agents, they must address the possible future state where total arrivals are significantly less. If the ECSS PMO staffs the help desk with 8 Level 1 and 8 Level 2 agents without a contingent for the probable high call volume scenarios, the help desk will fail to provide adequate service to the ECSS users.

A fixed long-run arrival rate at implementation is unlikely, so a strategy must be in place to handle peak usage of the ECSS help desk during operations, major exercises, and major releases. During these peaks, the ECSS help desks could see staffing requirements of over 31 agents, which is similar to the Navy ERP Level 2 help desk staffing level. Maintaining a facility to support these peaks could be inefficient since these agents would only be utilized during these unique situations. In this case, temporary on-site assistance and/or training might be the better alternative.

Comparison with Prior Research

Prior estimates from the ECSS PMO show Level 1 and 2 requirements of 16.1 and 16.4. The Air Force Cost Analysis Agency (AFCAA) estimated 11.8 and 14.3. Finally, the Air Force Logistics Management Agency (AFLMA) estimated 21.9 and 23.5. This study shows that about 12 agents for Level 1 and 12 agents for Level II would be optimal. Table 20 shows the four estimates and Table 21 compares the estimates with DEAMS and Navy ERP.

Table 20: Comparison of Estimates

	Level 1	Level 2
ECSS PMO	16.1	16.4
AFCAA	11.8	14.3
ALFMA	21.9	23.5
Initial	31	31
Steady State	12	12
Long Run	8	8

Table 21: Comparison of Other DoD ERP Systems

	Users	Level 1	Level 2	Users per lvl1 Agent	Users per lvl2 Agent
DEAMS	27,214	14.5	12.0	1,877	2,268
NAVY ERP	66,000	30.0	52.0	2,200	1,269
Initial	40,000	31	31	1,290	1,290
Steady State	40,000	12	12	3,333	3,333
Long Run	40,000	8	8	5,000	5,000

Sensitivity Analysis

The thesis tested the sensitivity of the recommended staffing levels. For the Level 2 help desk, this study testing the impact of higher and lower service rates, 20 minutes and 16 minutes. For the Level 1 help desk, this study testing the impact of higher and lower service rates, 10 minutes and 5 minutes. Finally, the study tested the impact of higher and lower renege times for Level 2 with 8 and 2 minutes.

In general, the results show that increased service rates will increase the load on the system; therefore, more agents are required to meet the same level of performance. The opposite remains true where a decreased service rate will decrease the load; therefore, wait time and reneges will decrease, but agent utilization will also decrease. Table 22 shows the details of the sensitivity analysis.

Table 22 Sensitivity Analysis

Scenario	Agents	Rep	Total Daily Calls	Service Rate (min)	Renege Time (min)	Avg Wait Time (sec)	Avg Wait Time (sec) 95% C.I.	Agent Utilization	Agent Utilization 95% CI	Renege %	Renege % 95% C.I.
Level 2	8	20	84	17.74	8	84.6	2.33	34.3%	0.10%	17.7%	0.5%
Level 2	8	20	84	17.74	2	24.8	0.62	32.6%	0.08%	20.8%	0.5%
Level 2	31	20	710	17.74	8	133.9	1.76	64.7%	0.12%	27.9%	0.4%
Level 2	31	20	710	17.74	2	35.3	0.38	63.0%	0.11%	29.5%	0.3%
Level 2	12	20	247	17.74	8	151.2	1.45	56.4%	0.06%	31.5%	0.3%
Level 2	12	20	247	17.74	2	41.4	0.28	53.6%	0.06%	34.4%	0.2%
Level 2	8	20	84	20	4	53.3	1.36	36.1%	0.07%	22.2%	0.5%
Level 2	8	20	84	17.74	4	46.8	1.40	33.2%	0.08%	19.4%	0.58%
Level 2	8	20	84	16	4	43.2	1.40	31.0%	0.08%	17.9%	0.6%
Level 2	31	20	710	20	4	79.6	0.64	67.2%	0.11%	33.1%	0.3%
Level 2	31	20	710	17.74	4	68.4	0.62	63.9%	0.09%	28.5%	0.26%
Level 2	31	20	710	16	4	58.7	0.96	60.9%	0.08%	24.5%	0.4%
Level 2	12	20	247	20	4	89.3	0.48	58.0%	0.06%	37.2%	0.2%
Level 2	12	20	247	17.74	4	79.6	0.56	54.8%	0.04%	33.1%	0.24%
Level 2	12	20	247	16	4	71.3	0.73	52.1%	0.04%	29.7%	0.3%
Level 1	8	20	210	10	4	60.8	1.06	44.2%	0.04%	25.4%	0.4%
Level 1	8	20	210	7.5	4	44.3	1.66	36.6%	0.13%	18.4%	0.69%
Level 1	8	20	210	5	4	13.3	0.44	25.4%	0.06%	5.6%	0.2%
Level 1	31	20	1775	10	4	96.8	0.37	74.4%	0.10%	40.3%	0.2%
Level 1	31	20	1775	7.5	4	68.8	0.85	66.9%	0.12%	28.7%	0.35%
Level 1	31	20	1775	5	4	16.6	0.42	54.2%	0.02%	6.8%	0.2%
Level 1	12	20	618	10	4	101.9	0.56	66.0%	0.08%	42.5%	0.2%
Level 1	12	20	618	7.5	4	77.0	1.04	58.8%	0.06%	32.1%	0.44%
Level 1	12	20	618	5	4	32.4	0.51	46.6%	0.03%	13.5%	0.2%

From the analysis, it appears that improvements in service time could add more value than adding additional agents to the help desks. A future study could compare the costs for training to improve performance and the costs of adding additional FTEs to reach the same goal.

Limitations of the Model

This study provided a detailed simulation of the ECSS help desk. The results provide similar estimates to prior efforts, but the model is limited to a few factors discussed below.

Queueing Theory Limitations

The model is limited to the assumptions of exponential distributions for arrival rates, service rates, and abandonment. If the FAS call center tracked individual call data, the assumptions could be verified. Another assumption that is not always reality is the assumption of homogeneous agents. A wider variance of service rates for individually modeled agents could influence the results. In many call centers, service agents specialize in certain issues. For example, the ECSS Level 2 help desk could have some agents that specialize in a group of modules while some specialize in software integration.

Simulation Limitations

The limitations of the simulation are data and inputs. Limited time was available to generate data. More iterations of the model would have increased the sample size and more combinations of staffing regimes, calls, service rates, and renege time would have provided added insight to the dynamics of the ECSS help desk.

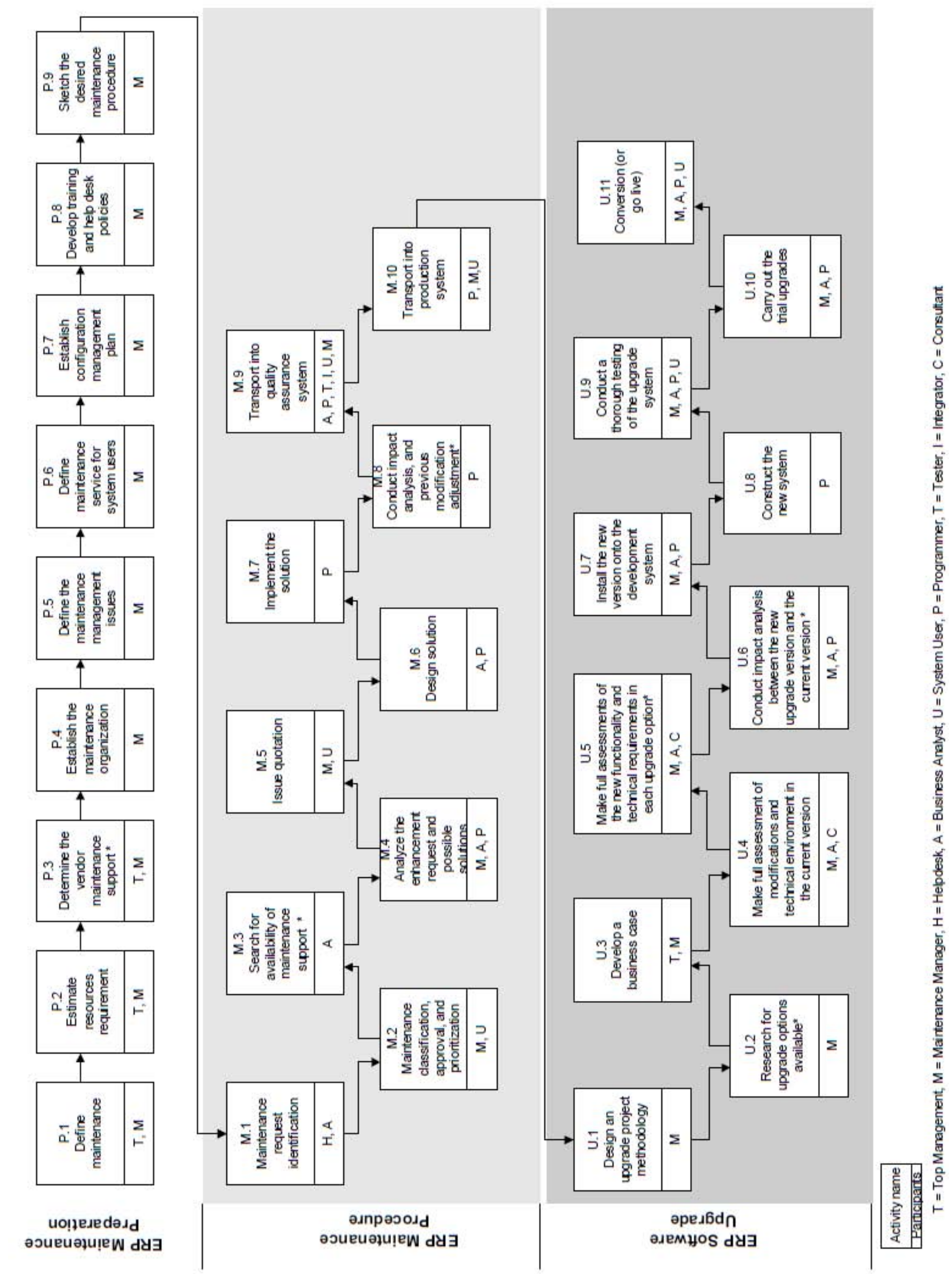
Final Thoughts and Future Research

Although the study has a few limitations, the positive outlook is that the ECSS team can update and manipulate the simulation model to reflect future scenarios for ECSS. If requirements change that would affect the model's inputs, analysts can use the simulation, and they can follow the methodology of this study to determine a new optimal solution and the expected performance of their decisions.

Once the Air Force implements ECSS release one, an interesting follow-on study would be to test, validate, and update the inputs of this study with operational call data. Among other research topics, researchers could study the impacts of investments in call

center staffing and technology with call center performance. Would investments in higher capable call center systems dramatically increase performance? What affect would robust highly capable help desk support have on training and sustainment requirements?

Appendix A: ERP Maintenance Model



(Sui Pui Ng et al., 2003)

Appendix B: M/M/S Formulas

Average number of customers in the system	
Average time a customer spends in the system	
Average number of customers waiting in the queue	
Average time a customer spends waiting in the queue	
Utilization factor for the system	
Probability of 0 customers in the system	

(Ragsdale, 2007)

Appendix C: M/M/1 Formulas

Average number of customers in the system	
Average time a customer spends in the system	$\frac{\quad}{\lambda}$
Average number of customers waiting in the queue	
Average time a customer spends waiting in the queue	
Utilization factor for the system	
Probability of 0 customers in the system	

(Ragsdale, 2007)

Appendix D: Calculated Calls Per Hour and MTBA

Time (Hours)	Worldwide Total %	Mean Call Arrivals/day 40.77	210.41	565.48	618.08	1,775.34	2,104.11	2,893.15	8,153.42
1:00 AM	1.84%	0.75	3.87	10.41	11.38	32.68	38.74	53.26	150.10
2:00 AM	1.36%	0.55	2.85	7.67	8.38	24.07	28.52	39.22	110.53
3:00 AM	1.01%	0.41	2.11	5.68	6.21	17.84	21.15	29.08	81.95
4:00 AM	1.04%	0.42	2.19	5.89	6.44	18.49	21.91	30.12	84.90
5:00 AM	1.11%	0.45	2.34	6.30	6.88	19.77	23.43	32.21	90.78
6:00 AM	0.99%	0.41	2.09	5.63	6.15	17.66	20.93	28.78	81.11
7:00 AM	0.89%	0.36	1.87	5.01	5.48	15.74	18.65	25.65	72.29
8:00 AM	1.31%	0.53	2.75	7.39	8.07	23.19	27.49	37.79	106.51
9:00 AM	2.87%	1.17	6.03	16.22	17.73	50.92	60.35	82.98	233.86
10:00 AM	5.25%	2.14	11.04	29.67	32.43	93.16	110.41	151.82	427.84
11:00 AM	7.05%	2.88	14.84	39.89	43.60	125.24	148.43	204.10	575.18
12:00 PM	7.49%	3.05	15.76	42.37	46.31	133.01	157.64	216.75	610.85
1:00 PM	7.35%	3.00	15.47	41.57	45.43	130.50	154.66	212.66	599.32
2:00 PM	6.88%	2.81	14.48	38.92	42.54	122.18	144.81	199.11	561.13
3:00 PM	7.41%	3.02	15.60	41.92	45.81	131.59	155.96	214.45	604.36
4:00 PM	7.96%	3.24	16.74	44.98	49.17	141.23	167.38	230.15	648.61
5:00 PM	7.63%	3.11	16.05	43.14	47.15	135.44	160.52	220.71	622.01
6:00 PM	6.84%	2.79	14.38	38.65	42.25	121.36	143.83	197.77	557.35
7:00 PM	5.71%	2.33	12.02	32.29	35.30	101.38	120.16	165.22	465.61
8:00 PM	4.64%	1.89	9.76	26.22	28.66	82.32	97.57	134.15	378.07
9:00 PM	3.89%	1.59	8.19	22.01	24.06	69.11	81.90	112.62	317.37
10:00 PM	3.50%	1.43	7.37	19.81	21.66	62.20	73.72	101.37	285.67
11:00 PM	3.24%	1.32	6.83	18.34	20.05	57.59	68.25	93.85	264.48
12:00 AM	2.74%	1.12	5.77	15.50	16.94	48.67	57.68	79.32	223.53

Time (Hours)	Mean time between arrivals (minutes)							
	40.77	**210.41**	**565.48**	**618.08**	**1,775.34**	**2,104.11**	**2,893.15**	**2,894.15**
1:00 AM	79.95	15.49	5.76	5.27	1.84	1.55	1.13	0.40
2:00 AM	108.56	21.03	7.83	7.16	2.49	2.10	1.53	0.54
3:00 AM	146.42	28.37	10.56	9.66	3.36	2.84	2.06	0.73
4:00 AM	141.35	27.39	10.19	9.32	3.25	2.74	1.99	0.71
5:00 AM	132.19	25.61	9.53	8.72	3.04	2.56	1.86	0.66
6:00 AM	147.94	28.66	10.67	9.76	3.40	2.87	2.08	0.74
7:00 AM	166.00	32.16	11.97	10.95	3.81	3.22	2.34	0.83
8:00 AM	112.66	21.83	8.12	7.43	2.59	2.18	1.59	0.56
9:00 AM	51.31	9.94	3.70	3.38	1.18	0.99	0.72	0.26
10:00 AM	28.05	5.43	2.02	1.85	0.64	0.54	0.40	0.14
11:00 AM	20.86	4.04	1.50	1.38	0.48	0.40	0.29	0.10
12:00 PM	19.64	3.81	1.42	1.30	0.45	0.38	0.28	0.10
1:00 PM	20.02	3.88	1.44	1.32	0.46	0.39	0.28	0.10
2:00 PM	21.39	4.14	1.54	1.41	0.49	0.41	0.30	0.11
3:00 PM	19.86	3.85	1.43	1.31	0.46	0.38	0.28	0.10
4:00 PM	18.50	3.58	1.33	1.22	0.42	0.36	0.26	0.09
5:00 PM	19.29	3.74	1.39	1.27	0.44	0.37	0.27	0.10
6:00 PM	21.53	4.17	1.55	1.42	0.49	0.42	0.30	0.11
7:00 PM	25.77	4.99	1.86	1.70	0.59	0.50	0.36	0.13
8:00 PM	31.74	6.15	2.29	2.09	0.73	0.61	0.45	0.16
9:00 PM	37.81	7.33	2.73	2.49	0.87	0.73	0.53	0.19
10:00 PM	42.01	8.14	3.03	2.77	0.96	0.81	0.59	0.21
11:00 PM	45.37	8.79	3.27	2.99	1.04	0.88	0.64	0.23
12:00 AM	53.68	10.40	3.87	3.54	1.23	1.04	0.76	0.27

Appendix E: Agents Required by Hour

Total Daily Arrivals	Mean Service rate (Min)
210.41	18.55

r	λ (PerHour)	µ (PerHour)	R	Beta	N	N Required
1	3.87	3.23	1.20	0.1	1.31	2
2	2.85	3.23	0.88	0.1	0.98	1
3	2.11	3.23	0.65	0.1	0.73	1
4	2.19	3.23	0.68	0.1	0.76	1
5	2.34	3.23	0.72	0.1	0.81	1
6	2.09	3.23	0.65	0.1	0.73	1
7	1.87	3.23	0.58	0.1	0.65	1
8	2.75	3.23	0.85	0.1	0.94	1
9	6.03	3.23	1.87	0.1	2.00	3
0	11.04	3.23	3.41	0.1	3.60	4
1	14.84	3.23	4.59	0.1	4.80	5
2	15.76	3.23	4.87	0.1	5.09	6
3	15.47	3.23	4.78	0.1	5.00	6
4	14.48	3.23	4.48	0.1	4.69	5
5	15.60	3.23	4.82	0.1	5.04	6
6	16.74	3.23	5.17	0.1	5.40	6
7	16.05	3.23	4.96	0.1	5.19	6
8	14.38	3.23	4.45	0.1	4.66	5
9	12.02	3.23	3.71	0.1	3.91	4
0	9.76	3.23	3.02	0.1	3.19	4
1	8.19	3.23	2.53	0.1	2.69	3
2	7.37	3.23	2.28	0.1	2.43	3
3	6.83	3.23	2.11	0.1	2.26	3
4	5.77	3.23	1.78	0.1	1.92	2

Total Daily Arrivals	Mean Service rate (Min)
618.08	18.55

Hr	λ (PerHour)	µ (PerHour)	R	Beta	N	N Required
1	11.38	3.23	3.52	0.1	3.71	4
2	8.38	3.23	2.59	0.1	2.75	3
3	6.21	3.23	1.92	0.1	2.06	3
4	6.44	3.23	1.99	0.1	2.13	3
5	6.88	3.23	2.13	0.1	2.27	3
6	6.15	3.23	1.90	0.1	2.04	3
7	5.48	3.23	1.69	0.1	1.82	2
8	8.07	3.23	2.50	0.1	2.65	3
9	17.73	3.23	5.48	0.1	5.71	6
10	32.43	3.23	10.03	0.1	10.34	11
11	43.60	3.23	13.48	0.1	13.85	14
12	46.31	3.23	14.32	0.1	14.69	15
13	45.43	3.23	14.05	0.1	14.42	15
14	42.54	3.23	13.15	0.1	13.51	14
15	45.81	3.23	14.16	0.1	14.54	15
16	49.17	3.23	15.20	0.1	15.59	16
17	47.15	3.23	14.58	0.1	14.96	15
18	42.25	3.23	13.06	0.1	13.42	14
19	35.30	3.23	10.91	0.1	11.24	12
20	28.66	3.23	8.86	0.1	9.16	10
21	24.06	3.23	7.44	0.1	7.71	8
22	21.66	3.23	6.70	0.1	6.95	7
23	20.05	3.23	6.20	0.1	6.45	7
24	16.94	3.23	5.24	0.1	5.47	6

Total Daily Arrivals	Mean Service rate (Min)
2,104.11	18.55

Hr	λ (PerHour)	µ (PerHour)	R	Beta	N	N Required
1	38.74	3.23	11.98	0.1	12.32	13
2	28.52	3.23	8.82	0.1	9.12	10
3	21.15	3.23	6.54	0.1	6.79	7
4	21.91	3.23	6.77	0.1	7.03	8
5	23.43	3.23	7.24	0.1	7.51	8
6	20.93	3.23	6.47	0.1	6.73	7
7	18.65	3.23	5.77	0.1	6.01	7
8	27.49	3.23	8.50	0.1	8.79	9
9	60.35	3.23	18.66	0.1	19.09	20
10	110.41	3.23	34.14	0.1	34.72	35
11	148.43	3.23	45.89	0.1	46.57	47
12	157.64	3.23	48.74	0.1	49.43	50
13	154.66	3.23	47.82	0.1	48.51	49
14	144.81	3.23	44.77	0.1	45.44	46
15	155.96	3.23	48.22	0.1	48.91	49
16	167.38	3.23	51.75	0.1	52.47	53
17	160.52	3.23	49.63	0.1	50.33	51
18	143.83	3.23	44.47	0.1	45.14	46
19	120.16	3.23	37.15	0.1	37.76	38
20	97.57	3.23	30.16	0.1	30.71	31
21	81.90	3.23	25.32	0.1	25.82	26
22	73.72	3.23	22.79	0.1	23.27	24
23	68.25	3.23	21.10	0.1	21.56	22
24	57.68	3.23	17.83	0.1	18.26	19

Total Daily Arrivals	Mean Service rate (Min)
210.41	7.50

Ir	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	3.87	8.00	0.48	0.1	0.55	1
2	2.85	8.00	0.36	0.1	0.42	1
3	2.11	8.00	0.26	0.1	0.32	1
4	2.19	8.00	0.27	0.1	0.33	1
5	2.34	8.00	0.29	0.1	0.35	1
6	2.09	8.00	0.26	0.1	0.31	1
7	1.87	8.00	0.23	0.1	0.28	1
8	2.75	8.00	0.34	0.1	0.40	1
9	6.03	8.00	0.75	0.1	0.84	1
0	11.04	8.00	1.38	0.1	1.50	2
1	14.84	8.00	1.86	0.1	1.99	2
2	15.76	8.00	1.97	0.1	2.11	3
3	15.47	8.00	1.93	0.1	2.07	3
4	14.48	8.00	1.81	0.1	1.94	2
5	15.60	8.00	1.95	0.1	2.09	3
6	16.74	8.00	2.09	0.1	2.24	3
7	16.05	8.00	2.01	0.1	2.15	3
8	14.38	8.00	1.80	0.1	1.93	2
9	12.02	8.00	1.50	0.1	1.62	2
0	9.76	8.00	1.22	0.1	1.33	2
1	8.19	8.00	1.02	0.1	1.12	2
2	7.37	8.00	0.92	0.1	1.02	2
3	6.83	8.00	0.85	0.1	0.95	1
4	5.77	8.00	0.72	0.1	0.81	1

Total Daily Arrivals	Mean Service rate (Min)
618.08	7.50

Hr	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	11.38	8.00	1.42	0.1	1.54	2
2	8.38	8.00	1.05	0.1	1.15	2
3	6.21	8.00	0.78	0.1	0.86	1
4	6.44	8.00	0.80	0.1	0.89	1
5	6.88	8.00	0.86	0.1	0.95	1
6	6.15	8.00	0.77	0.1	0.86	1
7	5.48	8.00	0.68	0.1	0.77	1
8	8.07	8.00	1.01	0.1	1.11	2
9	17.73	8.00	2.22	0.1	2.36	3
10	32.43	8.00	4.05	0.1	4.26	5
11	43.60	8.00	5.45	0.1	5.68	6
12	46.31	8.00	5.79	0.1	6.03	7
13	45.43	8.00	5.68	0.1	5.92	6
14	42.54	8.00	5.32	0.1	5.55	6
15	45.81	8.00	5.73	0.1	5.97	6
16	49.17	8.00	6.15	0.1	6.39	7
17	47.15	8.00	5.89	0.1	6.14	7
18	42.25	8.00	5.28	0.1	5.51	6
19	35.30	8.00	4.41	0.1	4.62	5
20	28.66	8.00	3.58	0.1	3.77	4
21	24.06	8.00	3.01	0.1	3.18	4
22	21.66	8.00	2.71	0.1	2.87	3
23	20.05	8.00	2.51	0.1	2.66	3
24	16.94	8.00	2.12	0.1	2.26	3

Total Daily Arrivals	Mean Service rate (Min)
2,104.11	7.50

Hr	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	38.74	8.00	4.84	0.1	5.06	6
2	28.52	8.00	3.57	0.1	3.75	4
3	21.15	8.00	2.64	0.1	2.81	3
4	21.91	8.00	2.74	0.1	2.90	3
5	23.43	8.00	2.93	0.1	3.10	4
6	20.93	8.00	2.62	0.1	2.78	3
7	18.65	8.00	2.33	0.1	2.48	3
8	27.49	8.00	3.44	0.1	3.62	4
9	60.35	8.00	7.54	0.1	7.82	8
10	110.41	8.00	13.80	0.1	14.17	15
11	148.43	8.00	18.55	0.1	18.99	19
12	157.64	8.00	19.70	0.1	20.15	21
13	154.66	8.00	19.33	0.1	19.77	20
14	144.81	8.00	18.10	0.1	18.53	19
15	155.96	8.00	19.50	0.1	19.94	20
16	167.38	8.00	20.92	0.1	21.38	22
17	160.52	8.00	20.06	0.1	20.51	21
18	143.83	8.00	17.98	0.1	18.40	19
19	120.16	8.00	15.02	0.1	15.41	16
20	97.57	8.00	12.20	0.1	12.55	13
21	81.90	8.00	10.24	0.1	10.56	11
22	73.72	8.00	9.22	0.1	9.52	10
23	68.25	8.00	8.53	0.1	8.82	9
24	57.68	8.00	7.21	0.1	7.48	8

Total Daily Arrivals	Mean Service rate (Min)				
210.41	**4.00**				
λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
3.87	15.00	0.26	0.1	0.31	1
2.85	15.00	0.19	0.1	0.23	1
2.11	15.00	0.14	0.1	0.18	1
2.19	15.00	0.15	0.1	0.18	1
2.34	15.00	0.16	0.1	0.20	1
2.09	15.00	0.14	0.1	0.18	1
1.87	15.00	0.12	0.1	0.16	1
2.75	15.00	0.18	0.1	0.23	1
6.03	15.00	0.40	0.1	0.47	1
11.04	15.00	0.74	0.1	0.82	1
14.84	15.00	0.99	0.1	1.09	2
15.76	15.00	1.05	0.1	1.15	2
15.47	15.00	1.03	0.1	1.13	2
14.48	15.00	0.97	0.1	1.06	2
15.60	15.00	1.04	0.1	1.14	2
16.74	15.00	1.12	0.1	1.22	2
16.05	15.00	1.07	0.1	1.17	2
14.38	15.00	0.96	0.1	1.06	2
12.02	15.00	0.80	0.1	0.89	1
9.76	15.00	0.65	0.1	0.73	1
8.19	15.00	0.55	0.1	0.62	1
7.37	15.00	0.49	0.1	0.56	1
6.83	15.00	0.46	0.1	0.52	1
5.77	15.00	0.38	0.1	0.45	1

	Total Daily Arrivals	Mean Service rate (Min)				
	618.08	**4.00**				
Hr	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	11.38	15.00	0.76	0.1	0.85	1
2	8.38	15.00	0.56	0.1	0.63	1
3	6.21	15.00	0.41	0.1	0.48	1
4	6.44	15.00	0.43	0.1	0.49	1
5	6.88	15.00	0.46	0.1	0.53	1
6	6.15	15.00	0.41	0.1	0.47	1
7	5.48	15.00	0.37	0.1	0.43	1
8	8.07	15.00	0.54	0.1	0.61	1
9	17.73	15.00	1.18	0.1	1.29	2
10	32.43	15.00	2.16	0.1	2.31	3
11	43.60	15.00	2.91	0.1	3.08	4
12	46.31	15.00	3.09	0.1	3.26	4
13	45.43	15.00	3.03	0.1	3.20	4
14	42.54	15.00	2.84	0.1	3.00	4
15	45.81	15.00	3.05	0.1	3.23	4
16	49.17	15.00	3.28	0.1	3.46	4
17	47.15	15.00	3.14	0.1	3.32	4
18	42.25	15.00	2.82	0.1	2.98	3
19	35.30	15.00	2.35	0.1	2.51	3
20	28.66	15.00	1.91	0.1	2.05	3
21	24.06	15.00	1.60	0.1	1.73	2
22	21.66	15.00	1.44	0.1	1.56	2
23	20.05	15.00	1.34	0.1	1.45	2
24	16.94	15.00	1.13	0.1	1.24	2

	Total Daily Arrivals	Mean Service rate (Min)				
	2,104.11	**4.00**				
Hr	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	38.74	15.00	2.58	0.1	2.74	3
2	28.52	15.00	1.90	0.1	2.04	3
3	21.15	15.00	1.41	0.1	1.53	2
4	21.91	15.00	1.46	0.1	1.58	2
5	23.43	15.00	1.56	0.1	1.69	2
6	20.93	15.00	1.40	0.1	1.51	2
7	18.65	15.00	1.24	0.1	1.36	2
8	27.49	15.00	1.83	0.1	1.97	2
9	60.35	15.00	4.02	0.1	4.22	5
10	110.41	15.00	7.36	0.1	7.63	8
11	148.43	15.00	9.90	0.1	10.21	11
12	157.64	15.00	10.51	0.1	10.83	11
13	154.66	15.00	10.31	0.1	10.63	11
14	144.81	15.00	9.65	0.1	9.96	10
15	155.96	15.00	10.40	0.1	10.72	11
16	167.38	15.00	11.16	0.1	11.49	12
17	160.52	15.00	10.70	0.1	11.03	12
18	143.83	15.00	9.59	0.1	9.90	10
19	120.16	15.00	8.01	0.1	8.29	9
20	97.57	15.00	6.50	0.1	6.76	7
21	81.90	15.00	5.46	0.1	5.69	6
22	73.72	15.00	4.91	0.1	5.14	6
23	68.25	15.00	4.55	0.1	4.76	5
24	57.68	15.00	3.85	0.1	4.04	5

Ir	Total Daily Arrivals	Mean Service rate (Min)				
	618.08	7.50				
Ir	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	11.38	8.00	1.42	0.1	1.54	2
2	8.38	8.00	1.05	0.1	1.15	2
3	6.21	8.00	0.78	0.1	0.86	1
4	6.44	8.00	0.80	0.1	0.89	1
5	6.88	8.00	0.86	0.1	0.95	1
6	6.15	8.00	0.77	0.1	0.86	1
7	5.48	8.00	0.68	0.1	0.77	1
8	8.07	8.00	1.01	0.1	1.11	2
9	17.73	8.00	2.22	0.1	2.36	3
0	32.43	8.00	4.05	0.1	4.26	5
1	43.60	8.00	5.45	0.1	5.68	6
2	46.31	8.00	5.79	0.1	6.03	7
3	45.43	8.00	5.68	0.1	5.92	6
4	42.54	8.00	5.32	0.1	5.55	6
5	45.81	8.00	5.73	0.1	5.97	6
6	49.17	8.00	6.15	0.1	6.39	7
7	47.15	8.00	5.89	0.1	6.14	7
8	42.25	8.00	5.28	0.1	5.51	6
9	35.30	8.00	4.41	0.1	4.62	5
0	28.66	8.00	3.58	0.1	3.77	4
1	24.06	8.00	3.01	0.1	3.18	4
2	21.66	8.00	2.71	0.1	2.87	3
3	20.05	8.00	2.51	0.1	2.66	3
4	16.94	8.00	2.12	0.1	2.26	3

	Total Daily Arrivals	Mean Service rate (Min)				
	618.08	7.50				
Hr	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	11.38	8.00	1.42	0.3	1.78	2
2	8.38	8.00	1.05	0.3	1.35	2
3	6.21	8.00	0.78	0.3	1.04	2
4	6.44	8.00	0.80	0.3	1.07	2
5	6.88	8.00	0.86	0.3	1.14	2
6	6.15	8.00	0.77	0.3	1.03	2
7	5.48	8.00	0.68	0.3	0.93	1
8	8.07	8.00	1.01	0.3	1.31	2
9	17.73	8.00	2.22	0.3	2.66	3
10	32.43	8.00	4.05	0.3	4.66	5
11	43.60	8.00	5.45	0.3	6.15	7
12	46.31	8.00	5.79	0.3	6.51	7
13	45.43	8.00	5.68	0.3	6.39	7
14	42.54	8.00	5.32	0.3	6.01	7
15	45.81	8.00	5.73	0.3	6.44	7
16	49.17	8.00	6.15	0.3	6.89	7
17	47.15	8.00	5.89	0.3	6.62	7
18	42.25	8.00	5.28	0.3	5.97	6
19	35.30	8.00	4.41	0.3	5.04	6
20	28.66	8.00	3.58	0.3	4.15	5
21	24.06	8.00	3.01	0.3	3.53	4
22	21.66	8.00	2.71	0.3	3.20	4
23	20.05	8.00	2.51	0.3	2.98	3
24	16.94	8.00	2.12	0.3	2.55	3

	Total Daily Arrivals	Mean Service rate (Min)				
	618.08	7.50				
Hr	λ (PerHour)	μ (PerHour)	R	Beta	N	N Required
1	11.38	8.00	1.42	0.7	2.26	3
2	8.38	8.00	1.05	0.7	1.76	2
3	6.21	8.00	0.78	0.7	1.39	2
4	6.44	8.00	0.80	0.7	1.43	2
5	6.88	8.00	0.86	0.7	1.51	2
6	6.15	8.00	0.77	0.7	1.38	2
7	5.48	8.00	0.68	0.7	1.26	2
8	8.07	8.00	1.01	0.7	1.71	2
9	17.73	8.00	2.22	0.7	3.26	4
10	32.43	8.00	4.05	0.7	5.46	6
11	43.60	8.00	5.45	0.7	7.08	8
12	46.31	8.00	5.79	0.7	7.47	8
13	45.43	8.00	5.68	0.7	7.35	8
14	42.54	8.00	5.32	0.7	6.93	7
15	45.81	8.00	5.73	0.7	7.40	8
16	49.17	8.00	6.15	0.7	7.88	8
17	47.15	8.00	5.89	0.7	7.59	8
18	42.25	8.00	5.28	0.7	6.89	7
19	35.30	8.00	4.41	0.7	5.88	6
20	28.66	8.00	3.58	0.7	4.91	5
21	24.06	8.00	3.01	0.7	4.22	5
22	21.66	8.00	2.71	0.7	3.86	4
23	20.05	8.00	2.51	0.7	3.61	4
24	16.94	8.00	2.12	0.7	3.14	4

Appendix F: Agent Schedule Linear Optimization

High Arrival Rate @ Low Service Rate

Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	20	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	35	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	15	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	3	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	15	
Agents used	13	13	13	13	13	13	13	13	20	35	50	50	50	50	50	53	68	53	38	38	38	38	38	35		Number of Agents
N Required	13	10	7	8	8	7	7	9	20	35	47	50	49	46	49	53	51	46	38	31	26	24	22	19		101

Moderate Arrival Rate @ Low Service Rate

Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	12	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	11	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	3	
Agents used	4	4	4	4	4	4	4	4	12	12	15	15	15	15	15	16	15	15	12	12	12	12	12	11		Number of Agents
N Required	4	3	3	3	3	3	2	3	6	11	14	15	15	14	15	16	15	14	12	10	8	7	7	6		31

Light Arrival Rate @ Low Service Rate

Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	4	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	2	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	2	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	2	
Agents used	2	2	2	2	2	2	2	2	4	4	6	6	6	6	6	8	6	6	4	4	4	4	4	2		Number of Agents
N Required	2	1	1	1	1	1	1	1	3	4	5	6	6	5	6	6	6	5	4	4	3	3	3	2		12

High Arrival Rate @ Mid Service Rate

Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	Number of Agents
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	8	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	15	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	7	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	6	
Agents used	6	6	6	6	6	6	6	6	8	15	21	21	21	21	21	22	29	22	16	16	16	16	16	15		
N Required	6	4	3	3	4	3	3	4	8	15	19	21	20	19	20	22	21	19	16	13	11	10	9	8		43

Moderate Arrival Rate @ Mid Service Rate

Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	Number of Agents
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	3	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	3	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	2	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	2	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	2	
Agents used	2	2	2	2	2	2	2	2	3	5	7	7	7	7	7	9	9	7	5	5	5	5	5	3		
N Required	2	2	1	1	1	1	1	2	3	5	6	7	6	6	6	7	7	6	5	4	4	3	3	3		14

Light Arrival Rate @ Mid Service Rate

Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	Number of Agents
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	2	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	
Agents used	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	4	4	2	2	2	2	2	2	1		
N Required	1	1	1	1	1	1	1	1	1	2	2	3	3	2	3	3	3	2	2	2	2	2	1	1		6

High Arrival Rate @ High Service Rate

Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	5	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	5	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	5	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	4	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	
Agents used	3	3	3	3	3	3	3	3	5	10	11	11	11	11	11	15	15	10	9	9	9	9	9	5		Number of Agents
N Required	3	3	2	2	2	2	2	2	5	8	11	11	11	10	11	12	12	10	9	7	6	6	5	5		23

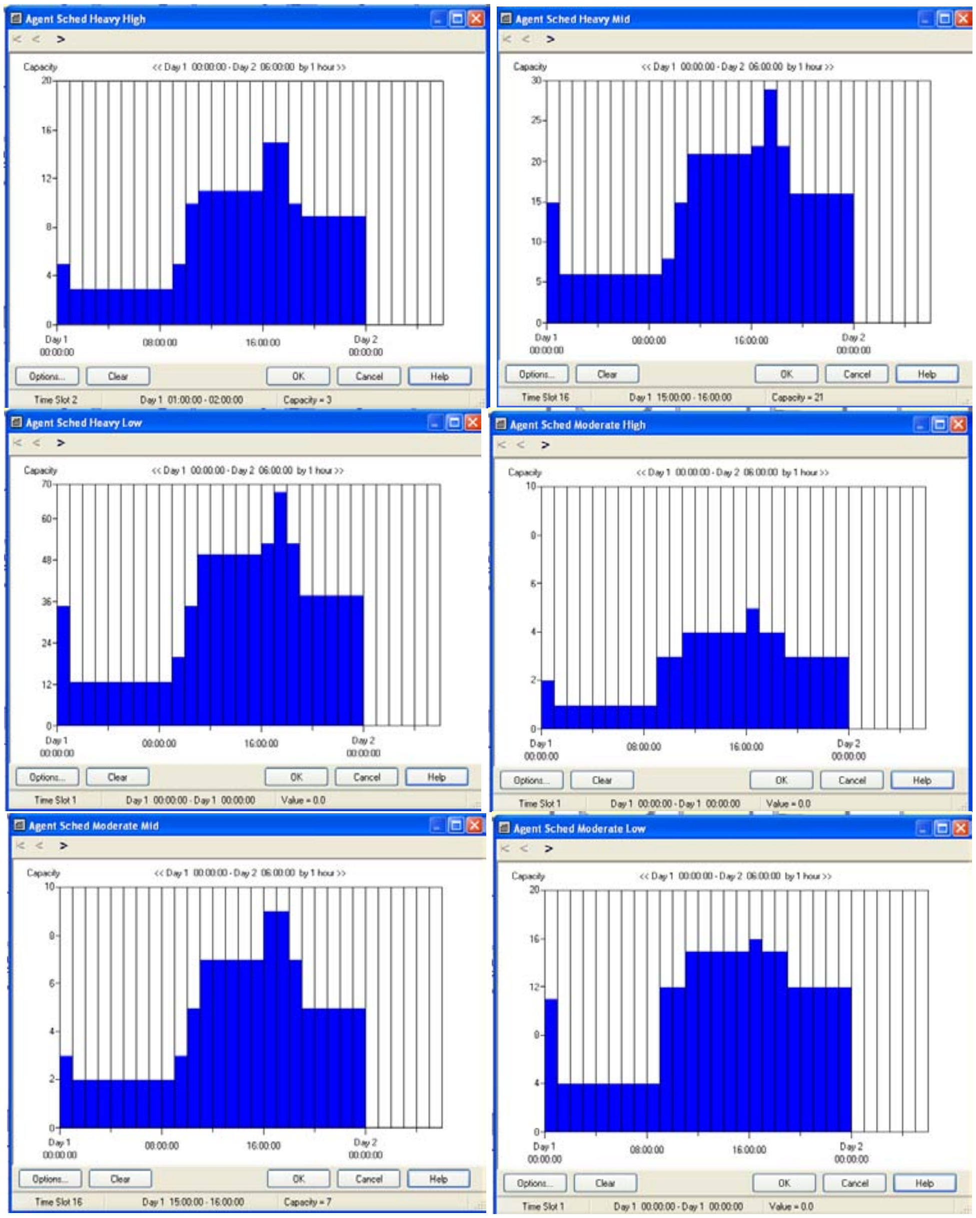
Moderate Arrival Rate @ High Service Rate

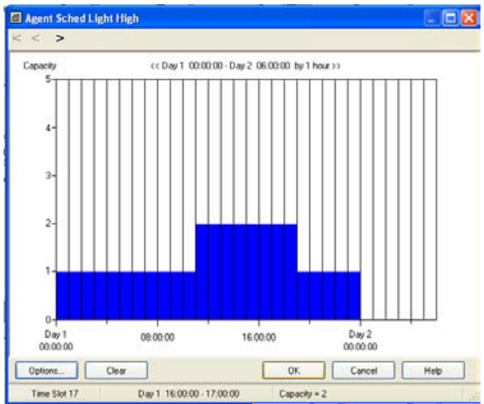
Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	3	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	2	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	
Agents used	1	1	1	1	1	1	1	1	3	3	4	4	4	4	4	5	4	4	3	3	3	3	3	2		Number of Agents
N Required	1	1	1	1	1	1	1	1	2	3	4	4	4	4	4	4	4	3	3	3	2	2	2	2		8

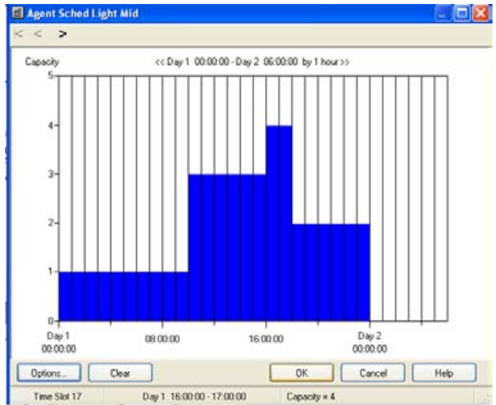
Light Arrival Rate @ High Service Rate

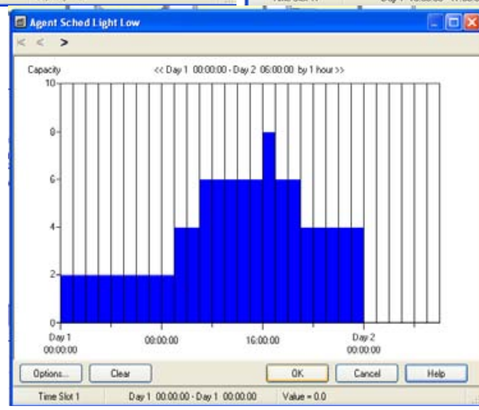
Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Workers Scheduled	
Shift 1 Binary	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	
Shift 2 Binary	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	
Shift 3 Binary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	
Booster Shift 1	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	
Booster Shift 2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	
Booster Shift 3	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	1	
Agents used	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1		Number of Agents
N Required	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1		4

Appendix G: Agent Schedules




Agent Sched Light High
<< Day 1 00:00:00 - Day 2 06:00:00 by 1 hour >>
Capacity
Day 1
00:00:00
08:00:00
16:00:00
Day 2
00:00:00
Options...
Clear
OK
Cancel
Help
Time Slot 17
Day 1 16:00:00 - 17:00:00
Capacity = 2


Agent Sched Light Mid
<< Day 1 00:00:00 - Day 2 06:00:00 by 1 hour >>
Capacity
Day 1
00:00:00
08:00:00
16:00:00
Day 2
00:00:00
Options...
Clear
OK
Cancel
Help
Time Slot 17
Day 1 16:00:00 - 17:00:00
Capacity = 4


Agent Sched Light Low
<< Day 1 00:00:00 - Day 2 06:00:00 by 1 hour >>
Capacity
Day 1
00:00:00
16:00:00
Day 2
00:00:00
Options...
Clear
OK
Cancel
Help
Time Slot 1
Day 1 00:00:00 - Day 1 00:00:00
Value = 0.0

Appendix H: Erlang C (M/M/S) Calculations

	Total Daily Calls	λ Arrival Rate per Hour	Avg Service Time (min)	μ Service Rate per Hour	Service Constant β	Square Root Safety	Instant Servers	Total Agents Per Day	Utilization	Avg time waiting in queue (min)
1	2,893.15	120.55	18.55	3.23	0.5	40.32	41	123	90.90%	2.22
2	2,893.15	120.55	18.55	3.23	0.5	40.32	41	123	90.90%	2.22
3	2,893.15	120.55	18.55	3.23	0.5	40.32	41	123	90.90%	2.22
4	2,893.15	120.55	7.50	8.00	0.5	17.01	18	54	83.71%	0.95
5	2,893.15	120.55	7.50	8.00	0.5	17.01	18	54	83.71%	0.95
6	2,893.15	120.55	7.50	8.00	0.5	17.01	18	54	83.71%	0.95
7	2,104.11	87.67	18.55	3.23	0.5	29.71	30	90	90.35%	3.11
8	2,104.11	87.67	18.55	3.23	0.5	29.71	30	90	90.35%	3.11
9	2,104.11	87.67	18.55	3.23	0.5	29.71	30	90	90.35%	3.11
10	1,775.34	73.97	18.55	3.23	0.5	25.26	26	78	87.96%	2.51
11	1,775.34	73.97	18.55	3.23	0.5	25.26	26	78	87.96%	2.51
12	1,775.34	73.97	18.55	3.23	0.5	25.26	26	78	87.96%	2.51
13	1,775.34	73.97	18.55	3.23	0.5	25.26	26	78	87.96%	2.51
14	1,775.34	73.97	18.55	3.23	0.5	25.26	26	78	87.96%	2.51
15	1,775.34	73.97	18.55	3.23	0.5	25.26	26	78	87.96%	2.51
16	2,104.11	87.67	7.50	8.00	0.5	12.61	13	39	84.30%	1.68
17	2,104.11	87.67	7.50	8.00	0.5	12.61	13	39	84.30%	1.68
18	2,104.11	87.67	7.50	8.00	0.5	12.61	13	39	84.30%	1.68
19	1,775.34	73.97	7.50	8.00	0.5	10.77	11	33	84.06%	2.08
20	1,775.34	73.97	7.50	8.00	0.5	10.77	11	33	84.06%	2.08
21	1,775.34	73.97	7.50	8.00	0.5	10.77	11	33	84.06%	2.08
22	1,775.34	73.97	7.50	8.00	0.5	10.77	11	33	84.06%	2.08
23	1,775.34	73.97	7.50	8.00	0.5	10.77	11	33	84.06%	2.08
24	1,775.34	73.97	7.50	8.00	0.5	10.77	11	33	84.06%	2.08
25	2,893.15	120.55	4.00	15.00	0.5	9.45	10	30	80.37%	0.85
26	2,893.15	120.55	4.00	15.00	0.5	9.45	10	30	80.37%	0.85
27	2,893.15	120.55	4.00	15.00	0.5	9.45	10	30	80.37%	0.85
28	618.08	25.75	18.55	3.23	0.5	9.37	10	30	79.62%	3.65
29	618.08	25.75	18.55	3.23	0.5	9.37	10	30	79.62%	3.65
30	618.08	25.75	18.55	3.23	0.5	9.37	10	30	79.62%	3.65
31	565.48	23.56	18.55	3.23	0.5	8.63	9	27	80.94%	4.90
32	565.48	23.56	18.55	3.23	0.5	8.63	9	27	80.94%	4.90
33	565.48	23.56	18.55	3.23	0.5	8.63	9	27	80.94%	4.90
34	2,104.11	87.67	4.00	15.00	0.5	7.05	8	24	73.06%	0.60
35	2,104.11	87.67	4.00	15.00	0.5	7.05	8	24	73.06%	0.60
36	2,104.11	87.67	4.00	15.00	0.5	7.05	8	24	73.06%	0.60
37	1,775.34	73.97	4.00	15.00	0.5	6.04	7	21	70.45%	0.60
38	1,775.34	73.97	4.00	15.00	0.5	6.04	7	21	70.45%	0.60
39	1,775.34	73.97	4.00	15.00	0.5	6.04	7	21	70.45%	0.60
40	1,775.34	73.97	4.00	15.00	0.5	6.04	7	21	70.45%	0.60

	Total Daily Calls	λ Arrival Rate per Hour	Avg Service Time (min)	μ Service Rate per Hour	Service Constant β	Square Root Safety	Instant Servers	Total Agents Per Day	Utilization	Avg time waiting in queue (min)
41	1,775.34	73.97	4.00	15.00	0.5	6.04	7	21	70.45%	0.60
42	1,775.34	73.97	4.00	15.00	0.5	6.04	7	21	70.45%	0.60
43	618.08	25.75	7.50	8.00	0.5	4.12	5	15	64.38%	1.24
44	618.08	25.75	7.50	8.00	0.5	4.12	5	15	64.38%	1.24
45	618.08	25.75	7.50	8.00	0.5	4.12	5	15	64.38%	1.24
46	565.48	23.56	7.50	8.00	0.5	3.80	4	12	73.63%	3.46
47	565.48	23.56	7.50	8.00	0.5	3.80	4	12	73.63%	3.46
48	565.48	23.56	7.50	8.00	0.5	3.80	4	12	73.63%	3.46
49	210.41	8.77	18.55	3.23	0.5	3.53	4	12	67.76%	5.68
50	210.41	8.77	18.55	3.23	0.5	3.53	4	12	67.76%	5.68
51	210.41	8.77	18.55	3.23	0.5	3.53	4	12	67.76%	5.68
52	210.41	8.77	18.55	3.23	0.5	3.53	4	12	67.76%	5.68
53	210.41	8.77	18.55	3.23	0.5	3.53	4	12	67.76%	5.68
54	210.41	8.77	18.55	3.23	0.5	3.53	4	12	67.76%	5.68
55	618.08	25.75	4.00	15.00	0.5	2.37	3	9	57.23%	1.00
56	618.08	25.75	4.00	15.00	0.5	2.37	3	9	57.23%	1.00
57	618.08	25.75	4.00	15.00	0.5	2.37	3	9	57.23%	1.00
58	565.48	23.56	4.00	15.00	0.5	2.20	3	9	52.36%	0.74
59	565.48	23.56	4.00	15.00	0.5	2.20	3	9	52.36%	0.74
60	565.48	23.56	4.00	15.00	0.5	2.20	3	9	52.36%	0.74
61	100.00	4.17	18.55	3.23	0.5	1.86	2	6	64.41%	13.15
62	100.00	4.17	18.55	3.23	0.5	1.86	2	6	64.41%	13.15
63	100.00	4.17	18.55	3.23	0.5	1.86	2	6	64.41%	13.15
64	210.41	8.77	7.50	8.00	0.5	1.62	2	6	54.79%	3.22
65	210.41	8.77	7.50	8.00	0.5	1.62	2	6	54.79%	3.22
66	210.41	8.77	7.50	8.00	0.5	1.62	2	6	54.79%	3.22
67	210.41	8.77	7.50	8.00	0.5	1.62	2	6	54.79%	3.22
68	210.41	8.77	7.50	8.00	0.5	1.62	2	6	54.79%	3.22
69	210.41	8.77	7.50	8.00	0.5	1.62	2	6	54.79%	3.22
70	210.41	8.77	4.00	15.00	0.5	0.97	1	3	58.45%	5.63
71	210.41	8.77	4.00	15.00	0.5	0.97	1	3	58.45%	5.63
72	210.41	8.77	4.00	15.00	0.5	0.97	1	3	58.45%	5.63
73	210.41	8.77	4.00	15.00	0.5	0.97	1	3	58.45%	5.63
74	210.41	8.77	4.00	15.00	0.5	0.97	1	3	58.45%	5.63
75	210.41	8.77	4.00	15.00	0.5	0.97	1	3	58.45%	5.63
76	100.00	4.17	7.50	8.00	0.5	0.88	1	3	52.08%	8.15
77	100.00	4.17	7.50	8.00	0.5	0.88	1	3	52.08%	8.15
78	100.00	4.17	7.50	8.00	0.5	0.88	1	3	52.08%	8.15
79	100.00	4.17	4.00	15.00	0.5	0.54	1	3	27.78%	1.54
80	100.00	4.17	4.00	15.00	0.5	0.54	1	3	27.78%	1.54
81	100.00	4.17	4.00	15.00	0.5	0.54	1	3	27.78%	1.54

Appendix I: Erlang C (M/M/S) Simulation

Agents	Rep	Total Daily Calls	Service Rate	Avg Wait Time (sec)	Avg Wait Time (sec) 95% CI	Agent Utilization	Agent Utilization 95% CI	Serviced	Serviced 95% C.I.
4	20	100	4	14.4	0.6	0.131	0.03%	233,033	242.1
4	20	100	7.5	223.2	16.9	0.269	0.26%	232,888	185
4	20	100	18.5	6,429.6	94.5	0.648	0.16%	232,911	204.4
4	20	210.41	4	158.4	7.0	0.3	0.13%	496,430	262
4	20	210.41	7.5	3,974.4	141.8	0.579	0.23%	496,456	369.7
6	20	100	4	14.4	0.6	0.131	0.03%	233,033	242.1
6	20	100	7.5	223.2	16.9	0.269	0.26%	232,888	185
6	20	100	18.5	6,429.6	94.5	0.648	0.16%	232,911	204.4
6	20	210.41	4	158.4	7.0	0.3	0.13%	496,430	262
6	20	210.41	7.5	3,974.4	141.8	0.579	0.23%	496,456	369.7
12	20	100	4	-	0.0	0.062	0.01%	232,983	204
12	20	100	7.5	-	0.1	0.117	0.02%	232,921	202.6
12	20	100	18.5	230.4	25.8	0.319	0.29%	232,955	227.8
12	20	210.41	4	-	0.0	0.133	0.02%	496,383	266.3
12	20	210.41	7.5	21.6	1.4	0.259	0.07%	496,457	221.5
12	20	210.41	18.5	5,932.8	78.2	0.677	0.09%	496,399	298.8
12	20	565.48	4	86.4	5.7	0.381	0.09%	1,338,589	536.6
8	20	210.41	4	-	0.0	0.053	0.01%	496,399	254.3
8	20	210.41	7.5	-	0.0	0.098	0.01%	496,421	252.2
8	20	210.41	18.5	3.6	0.3	0.245	0.05%	496,384	259.3
8	20	618.08	4	-	0.0	0.156	0.01%	1,463,472	586.8
8	20	618.08	7.5	3.6	0.4	0.295	0.07%	1,463,569	640.6
8	20	1775.34	4	36.0	4.7	0.459	0.10%	4,208,112	825.4
14	20	210.41	4	-	0.0	0.117	0.02%	496,394	245.1
14	20	210.41	7.5	10.8	1.5	0.226	0.11%	496,484	259.2
14	20	210.41	18.5	4,197.6	88.7	0.599	0.14%	496,174	327.3
14	20	618.08	4	79.2	5.3	0.367	0.09%	1,463,552	659.6
31	20	210.41	4	-	0.0	0.053	0.01%	496,399	254.3
31	20	210.41	7.5	-	0.0	0.098	0.01%	496,421	252.2
31	20	210.41	18.5	3.6	0.3	0.245	0.05%	496,384	259.3
31	20	618.08	4	-	0.0	0.156	0.01%	1,463,472	586.8
31	20	618.08	7.5	3.6	0.4	0.295	0.07%	1,463,569	640.6
31	20	1775.34	4	36.0	4.7	0.459	0.10%	4,208,112	825.4
23	20	1775.34	4	-	0.0	0.142	0.01%	4,208,081	751
23	20	1775.34	7.5	-	0.0	0.266	0.01%	4,208,220	825.2
23	20	2104.11	4	-	0.0	0.169	0.01%	4,987,938	858.4
23	20	2893.15	4	-	0.0	0.23	0.46%	6,792,876	1.36E+05
43	20	1775.34	4	3.6	0.1	0.332	0.02%	4,208,183	889.3
43	20	2104.11	4	10.8	0.6	0.394	0.04%	4,987,971	723.4

Appendix J: Blue Dart

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Saving Time and Money Through Efficient Help Desk Planning

Innovation fuels change. In 2003, the Secretary of Defense established six transformational initiatives to optimize performance and improve efficiency across the Department of Defense. The Air Force responded with the Expeditionary Logistics for the 21st Century (eLog21) campaign plan. ELog21 drove the implementation for an Enterprise Resource Planning (ERP) system. The Expeditionary Combat Support System (ECSS) is the Air Force's ERP solution.

A lot of literature focuses on the implementation of ERP systems, but there is a growing trend on ERP sustainment. Training and user support are a critical components to successful ERP implementations and sustainment. Analyzing the ECSS help desk and projecting staffing requirement are critical because it will affect the ability to provide support to users.

Help desks are classic queueing theory problems, and the Erlang C model is among the favorite models to use. Unfortunately, the Erlang C model has a reputation to overestimate staffing requirements. This study applies the Erlang A model through simulation, which accounts for the dynamics of customers who abandon their place in the queue.

The results of this study show that staffing the level 1 and 2 tier help desks with 12 full time equivalents (FTE) each will yield the most efficient balance of customer wait times, call center agent utilization, and minimum abandonment. The lasting impact that this study provides is a cost effective and reliable alternative method to estimate call center requirements for the Air Force.

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14. ABSTRACT During steady states, the Level 1 help desk might expect about 500 to 600 calls per month. That is about 0.39 to 0.46 calls per user per month, which represents the workload once ECSS is established and most of the users have already received training for the system. The optimal level for this workload is about 12 agents to operate the entire 24 hour period. At this level, the Level 1 help desk would minimize the amount of customers that renege from the system to about 15 to 22 percent and still maintain acceptable utilization percentages of about 52% to 59% while keeping the average wait time under a minute.The Level 2 help desk will experience similar environments like the Level 1 help desk. The major differences are that the Level 2 help desk would see lower call volumes since only about 40% of Level 1 calls are passed on the Level 2; and that the Level 2 help desk will have a longer average service rate. The simulation shows that the optimal staffing level is about 12. The simulation shows average wait times about 1 to 2.6 minutes, utilization from 47% to 60%, and 12% to 33% of customers that would renege.

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